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Detecting COVID-19 in chest X-ray images

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ABSTRACT

One reliable way of detecting coronavirus disease 2019 (COVID-19) is using a chest x-ray image due to its complications in the lung parenchyma. This paper proposes a solution for COVID-19 detection in chest x-ray images based on a convolutional neural network (CNN). This CNN-based solution is developed using a modified InceptionV3 as a backbone architecture. Self-attention layers are inserted to modify the backbone such that the number of trainable parameters is reduced and meaningful areas of COVID-19 in chest x-ray images are focused on a training process. The proposed CNN architecture is then learned to construct a model to classify COVID-19 cases from non-COVID-19 cases. It achieves sensitivity, specificity, and accuracy values of 93%, 96%, and 96%, respectively. The model is also further validated on the so-called other normal and abnormal, which are non-COVID-19 cases. Cases of other normal contain chest x-ray images of elderly patients with minimal fibrosis and spondylosis of the spine, whereas other abnormal cases contain chest x-ray images of tuberculosis, pneumonia, and pulmonary edema. The proposed solution could correctly classify them as non-COVID-19 with 92% accuracy. This is a practical scenario where non-COVID-19 cases could cover more than just a normal condition.

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1. INTRODUCTION

Coronavirus disease 2019 (COVID-19) has been an ongoing global pandemic since 2019. One of the effective ways to reduce the spread of this epidemic is to detect infected persons. Then, they must be quarantined to have less contact with others till they recover. One trustable method to measure COVID-19 is to notice a disease signal in a chest x-ray image because it usually causes complications in lung parenchyma [1], existing methods of detecting COVID-19 in a chest x-ray image were developed using a CNN. This paper is divided into two categories: i) newly designed CNN architecture-based methods and ii) well-known CNN architecture-based methods.

Recent methods are summarized in the first category of newly designed CNN architecture-based methods. In 2020, the 18 layers residual CNN [2], which was pre-trained using the ImageNet dataset, was proposed to construct the COVID-19 detection model in chest x-ray images [3]. It was evaluated with 100 chest x-ray images of 70 cases and 1,431 chest x-ray images of 1,008 cases. It achieved a high sensitivity of 96% but a relatively low specificity of 71%. Then in [4], instead of classifying chest x-ray images into two classes, they were classified into three classes: i) normal or no infection, ii) COVID-19 viral infection, and iii) other infections such as viral and bacterial diseases. The method was developed based on a design of a lightweight residual, including five convolutional layers of first-stage projection (1×1 convolutions), expansion (1×1 convolutions), depth-wise representation (3×3 convolutions), second-stage projection (1×1 convolutions), and extension (1×1 convolutions). It could classify non-COVID-19 classes efficiently since they were further split into two classes. However, the sensitivity was at a level of 91%.

In addition, the CNN architecture proposed in [5] contained four convolutional layers and three capsule layers to classify chest x-ray images into four classes: i) normal, ii) bacterial, iii) non-COVID viral, and iv) COVID-19. In [6], lightweight CNN architectures were attempted instead of highly-complex CNN architectures, including MobileNetV2, ShuffleNetV2, and SqueezeNet. The well-known CNN architectures were also attempted in [7], where VGG-19 and DenseNet-161 reported the highest performances. In 2021, the CoroDet was proposed based on a 22-layer CNN architecture [8]. It was trained under three scenarios of 2 classes (COVID-19 and normal), three classes (COVID-19, normal, and pneumonia), and four classes (COVID-19, normal, viral pneumonia, and bacterial pneumonia). Similarly, in [9], the proposed model consisted of a 10-layer CNN architecture for predicting COVID-19 and normal chest X-ray images. The dataset was preprocessed using a histogram equalizer before training. In contrast, the k-nearest neighbors method (KNN) was proposed in [10] by using a combination of feature extraction such as Haralick, histogram, and local binary pattern (LBP). The model used CT scan images to classify COVID-19 and non-COVID. The results outperformed CNN based model by 4.3%.

In 2022, the hybrid approach was proposed [11]. The model was composed of CNN as the feature extraction and long short-term memory (LSTM) for classifying chest x-ray images into three classes: normal, COVID-19, and pneumonia. In [12], the proposed method consisted of a 15-layer CNN architecture. The model was trained on 112 chest x-ray images which consisted of 56 normal images and 56 COVID-19 images. In addition, the 17-layer CNN architecture was proposed for COVID-19 classification into three classes: normal, pneumonia, and COVID-19 [13].

Recent methods are also summarized in the second category of well-known CNN architecture-based methods. In [14], five well-known pre-trained CNN-based models were attempted for detecting COVID-19 in chest x-ray images, including ResNet50, ResNet101, ResNet152, InceptionV3, and Inception-ResNetV2). The COVID-19 class was separated from the other classes of normal and viral pneumonia and bacterial pneumonia. Similarly, the method proposed in [15] also implemented the solutions based on five well-known CNN architectures of VGG19, MobileNet v2, Inception, Xception, and Inception ResNet v2. ResNet50 was reported to be the best solution in [14] while MobileNet v2 achieved the best performance in [15]. While, Hemdan *et al.* [16] attempted on using 7 popular CNN architectures of VGG19, DenseNet121, InceptionV3, ResNetV2, Inception-ResNet-V2, Xception, and MobileNetV2. Two of them were reported to achieve the best performances, which were VGG19 and DenseNet201.

In addition, the DeTraC transformation CNN-based model with pre-trained weights using ImageNet was applied as the backbone architecture [17]. In contrast, this paper only used the CNN model to extract chest x-ray images' features. Principal component analysis (PCA) was then used to reduce the dimension of the features, and the nearest centroid based on squared Euclidean distance was used as the classifier. At the same time, the method in [18] concluded that SqueezeNet achieved the best performance compared with the other three architectures of ResNet18, ResNet50, and DenseNet-121. In [19], the DenseNet-121, which was pre-trained using the ChestX-ray14 dataset [20], called CheXNet, was applied. Moreover, the weights were pretrained using the ImageNet dataset on the inception, and Resnet50 architectures were used in [21], [22], respectively.

In 2021, the three models based on Inception V3, Xception, and ResNeXt were attempted to classify chest x-ray images into three classes: normal, COVID-19, and pneumonia [23]. It achieved 97% precision in the COVID-19 class but dropped to 91% for the normal class. In [23], five CNN models were tried to extract features from chest x-ray images, including ResNet18, ResNet50, ResNet101, VGG16, and VGG19. Then, the support vector machine (SVM) was used as a classifier, with various attempts of several kernel functions of linear, quadratic, cubic, and Gaussian. In [24], the method was developed using ResNet8 to detect three COVID-19, bacterial pneumonia, and normal classes. GAN was used as the data augmentation technique to generate synthetic images in the training phase. In [25], the ResNet-101 architecture was applied to develop the main model. It used a large size of 1500×1500 x-ray images as the input. The heatmap was computed to demonstrate COVID-19 areas in a chest x-ray image. The lung area segmented based on U-Net was used to crop the resulted heatmap. In [26], six well-known pre-trained CNN-based models were evaluated including VGG16, InceptionV3, Xception, DenseNet201, InceptionResNetV2, and EfficientNetB4 for classifying 3 classes of normal, COVID-19, and Pneumonia on chest x-ray images. The result showed that EfficientNetB4 achieved the highest performance of 96%.

In 2022, Resnet-50 was selected as the base CNN architecture for classifying COVID-19 on chest x-ray images [27]. The proposed model applied transfer learning and evaluated two classification scenarios, i.e., binary (COVID-19 vs. normal) and multi-class (COVID-19 vs. normal vs. pneumonia). Similar to [28], Resnet-50 achieved the highest classification result compared with other CNN architectures, including

MobileNet V2, Inception V3, and DensNet-201 on chest x-ray images for two classes (COVID-19 vs. normal). In contrast, eight well-known pre-trained CNN-based models were evaluated for COVID-19 using Chest CT images [29]. The results showed that MobileNet V2 was the most accurate in COVID-19 detection.

In this paper, our proposed method also belongs to the second category, called Covid-AttNet. It is based on parts of InceptionV3 architecture, including only two main blocks. Some parts of the architecture are removed to reduce the complexity of the training, where a sufficient number of COVID-19 chest x-ray images could not be obtained. Also, the architecture is modified by inserting self-attention layers. The attention layers could help reduce the number of CNN parameters needed to be trained and better focus on meaningful information to detect a signal of COVID-19 in a chest x-ray image. The proposed model is trained to classify chest x-ray images into two classes COVID-19 and non-COVID-19. In addition, the trained model is further evaluated with other normal and abnormal cases belonging to the class of non-COVID-19. The other normal cases are chest x-ray images of elderly patients with minimal fibrosis and spondylosis of the spine, whereas the other abnormal cases are chest x-ray images with tuberculosis, pneumonia, and pulmonary edema.

The main technical contribution of this paper is to modify an original backbone architecture by extending it with self-attention layers. Suitable locations in the architecture of such extensions are also investigated. This mainly focuses on improving the architecture to emphasize traces of COVID-19 in chest x-ray images, which could be very small. The proposed solution could also reduce the number of learning parameters. This would then reduce training times and processing power and resources.

The rest of this paper is organized as. Section 2 proposes the research method of measuring COVID-19 in chest x-ray images. Section 3 explains experimental results and discussions. Then, section 4 draws up conclusions.

2. RESEARCH METHOD

This section explains an overview framework of our proposed method for detecting COVID-19 in chest x-ray images, as shown in Figure 1. In the data preparation process, chest x-ray images are re-sized and split into training, validating, and testing datasets. Then, images in the training dataset are augmented using real-time augmentations, including horizontal flip, rotation, and zooming. The training dataset with its augmented images is shuffled and batched to train the COVID-19 detection model. Each epoch is validated using validation images until it reaches the last epoch. The final output is a trained model called Covid-ConvAttnNet model. During the testing process, test images are re-sized and fed into the Covid-ConvAttnNet to generate corresponding prediction results, including output labels and their scores. The details are explained in the following subsections.

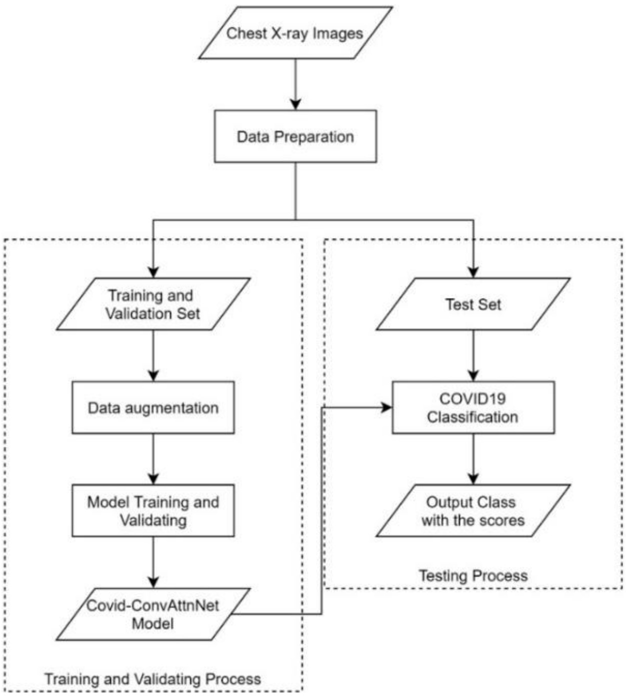

Figure 1. The overview framework of the proposed method

The COVID-19 detection model is constructed in this paper using the convolution neural network (CNN) architecture and the transfer learning technique. The InceptionV3 [30] is applied as the base classification model. It is a complex network composed of several Inception modules containing over 20 million parameters. In order to avoid overfitting on a small dataset and to reduce a model's complexity, a few InceptionV3 layers are selected and employed, including Inception-Module A and Module B. Inception Module A and Module B contain a small building block of convolutional layers and average pooling layers, as shown in Figures 2 to 4.

Over the past few years, several studies have applied an attention technique from machine translation to image classification and object detection. Based on our literature reviews, attention blocks can be applied as an additional layer or as a replacement for convolutional layers. The performance is comparable to solely convolution with a small number of model parameters. Therefore, the attention mechanism [31] is adopted as the extension of the base model, as shown in Figure 5.

As shown in Figure 2, the primary network used in the proposed method is based on the Inception Net V3 [32], with the RMSProp optimizer and factorized 7×7 convolutions. The label smoothing regularization is applied to prevent the overfitting of the network. Following the input layer, there are three convolutional layers, one max pooling layer, three convolutional layers, three Module A layers, five Module B layers, one average pooling layer, and one dense layer. The attention layer is inserted between the last Module B layer and the only average pooling layer.

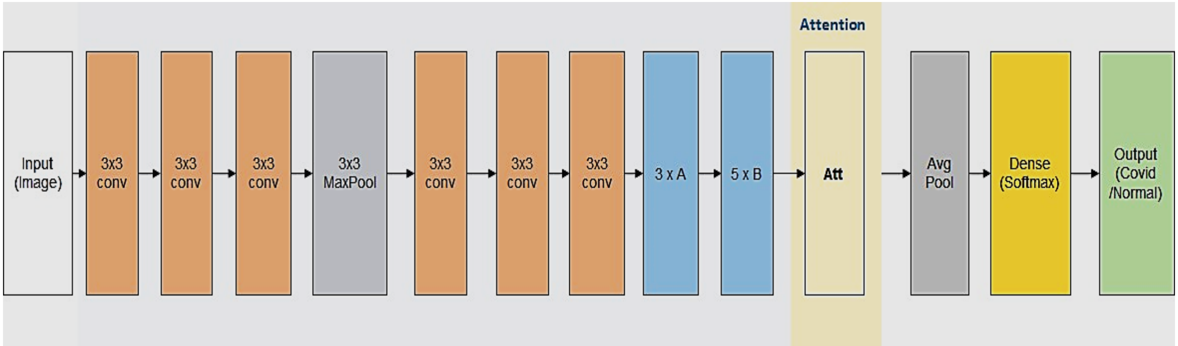

Figure 2. The overview of the proposed CNN-based architecture

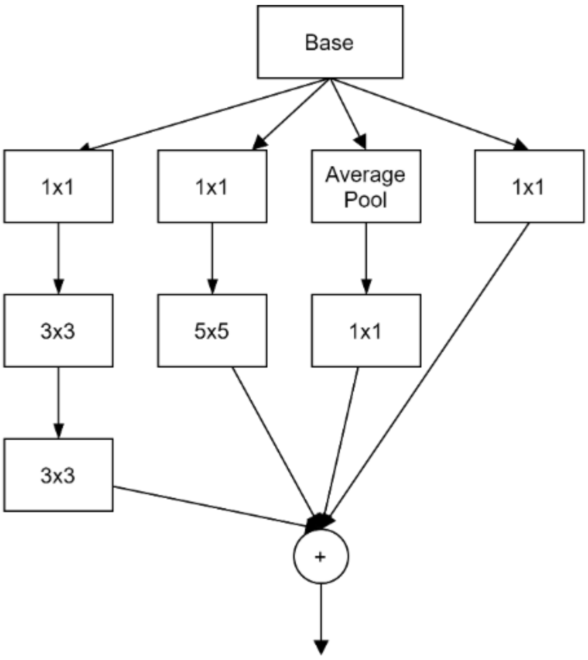

Figure 3. Inception A block used in the proposed CNN-based architecture

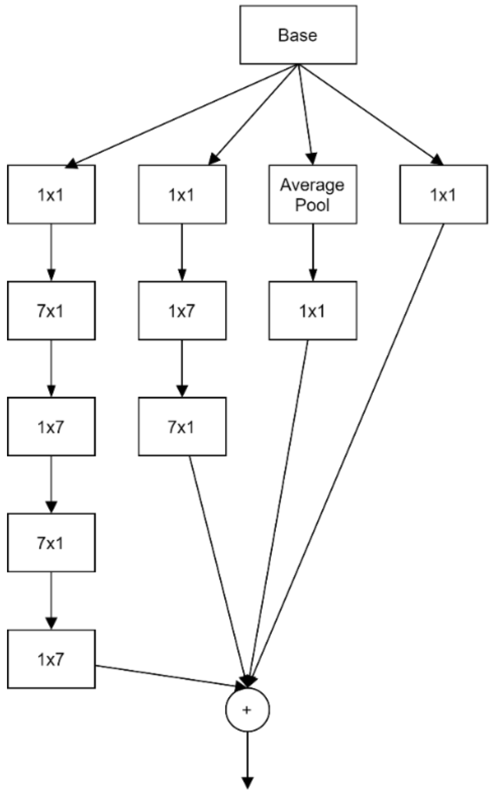

Figure 4. Inception B block used in the proposed CNN-based architecture

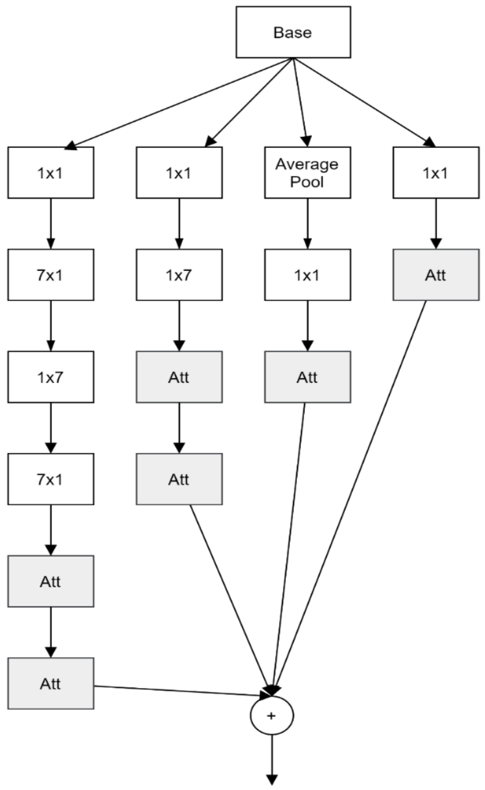

Figure 5. An attention layer proposed in Inception Module B

Each Module A, as shown in Figure 3, contains four chains of convolutional layers, followed by the ReLU. In addition, the 1×1 convolutional layer is applied at the beginning of the block to confirm that input and output dimensions must be the same [33], while in each Module B, asymmetric convolutions are applied to factorize convolutional layers from $n \times n$ into an $n \times 1$ followed by a $1 \times n$. This could significantly reduce the network's complexity, e.g., 71% of the total loads when n is 7. Based on our experiment, Module C is not included in our proposed framework because the high dimensional representation is not needed in this problem domain of COVID-19 detection. It increases the network complexity but could not lift the final detection result on top of Modules A and B.

In addition, self-attention layers [34], [35] are applied to each chain of the inception Module B, as shown in Figure 5. It could significantly reduce the number of model parameters and image processing power [36], [37]. It is based on the concept that the network could better focus on relevant parts of meaningful information for achieving a target, whereas it pays less attention to other parts [38], [39]. Each self-attention layer contains single-head attention computed on a memory block of small neighborhood pixels. It allows n inputs to interact with each other and return n outputs with attention scores.

3. RESULTS AND DISCUSSION

This section explains and discusses experimental results. Our proposed method is validated on our collected dataset containing 142 images of COVID-19 cases and 5,218 images of normal cases. The dataset of these two classes is split into the training, validating, and testing sets.

- A training set: 100 images of the COVID-19 class and 100 images of the normal class.
- A validating set: 12 images of the COVID-19 class and 12 images of the normal class.
- A testing set: 30 images of the COVID-19 class and 5,106 images of the normal class.

The proposed network is empirically trained with the batch size=10, the number of epochs=50, and the image size=600×600 pixels. The training and validating accuracies and losses are shown in Figure 6. In addition, the sensitivity (%), specificity (%), and accuracy (%) are reported in Table 1. The proposed method achieves 93%, 96%, and 96% sensitivity, specificity, and accuracy, respectively. It could perform well in normal cases, leading to a high value of specificity. The attention layer could enhance the sensitivity of the proposed method by assisting the network to focus better on COVID-19 signals in chest x-ray images. It, therefore, improves the sensitivity of measuring COVID-19 cases. In addition, the existing methods, including the proposed method, could not be directly compared because they are validated on different datasets, which could not be freely published due to the privacy of the patient data. However, the reported results could be concluded that the performance of the proposed method is comparable to the state-of-the-art, as shown in Table 1.

The results in Table 1 are measured on chest x-ray images with pure COVID-19 and pure normal without any other disease. Then, the trained model is further evaluated with other normal and other abnormal cases. The other normal class contains 100 chest x-ray images of elderly patients with minimal fibrosis and spondylosis of the spine. The proposed method achieves 70% accuracy on this other normal class. While the other abnormal class contains 100 chest x-ray images with tuberculosis, pneumonia, and pulmonary edema. The proposed method achieves 92% accuracy on this other abnormal class. The remaining 8% is incorrectly classified as COVID-19.

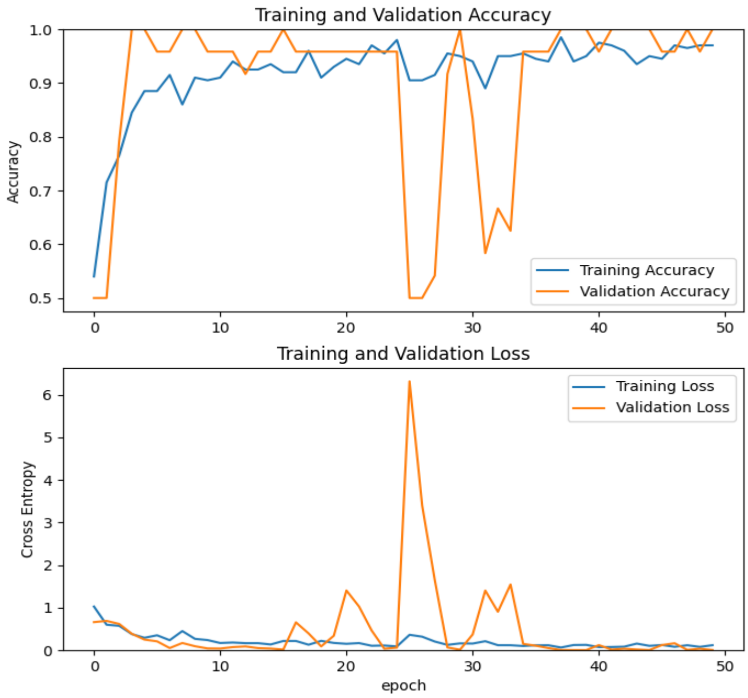

Figure 6. The training and validating accuracies and losses

Table 1. Experimental comparisons

Method	Dataset	Sensitivity (%)	Specificity (%)	Accuracy (%)
Zhang *et al.* [40]	100 images of COVID-19 and 1,431 images of pneumonia	96	71	95
Wang *et al.* [4]	183 images of COVID-19 and 8,066 patient cases with no pneumonia and 5,538 patient cases with non-COVID-19 pneumonia	87	99	93
Narin *et al.* [14]	50 images of COVID-19 and 50 images of normal	100	-	98
Apostolopoulos and Mpesiana [15]	224 images of COVID-19 and 700 images of common bacterial pneumonia and 504 images of normal	99	97	93
Hemdan *et al.* [16]	25 images of COVID-19 and 25 images of normal	-	-	90
Abbas *et al.* [17]	105 images of COVID-19 and 80 images of normal and 11 images of SARS	98	92	95
Khan *et al.* [21]	284 images of COVID-19 and 310 images of normal and 330 images of pneumonia bacterial and 327 images of pneumonia viral	-	-	90
Hall *et al.* [22]	135 images of COVID-19 and 320 images of viral and bacterial pneumonia	83	98	94
Minaee *et al.* [18]	40 images of COVID-19 and 3,000 images of normal	97	98	-
Mangal *et al.* [19]	165 images of COVID-19 and 1,583 images of normal	100	-	91
Bukhari *et al.* [41]	89 images of COVID-19 and 93 images of lungs without any radiological abnormality and 96 images with pneumonia caused by other pathogens	-	-	98
The proposed covid ConvAttnNet	142 images of COVID-19 and 5,218 images of normal	93	96	96

4. CONCLUSION

This paper presents a method of the CNN-based COVID-19 classification in chest x-ray images. Modules A and B of InceptionV3 are adopted in the proposed backbone architecture. The self-attention layers are added between Module B and the only average pooling layer. The designed architecture is trained from scratch to classify chest x-ray images into two classes COVID-19 and non-COVID-19. The attention layers are shown to improve the sensitivity of measuring COVID-19 cases. It could achieve 93% sensitivity and 96% for both specificity and accuracy values. When tested with the other normal scenario, 30% of chest x-ray images of elderly patients with minimal fibrosis and spondylosis of the spine are incorrectly classified as COVID-19. While for the other abnormal scenario, 8% of chest x-ray images with tuberculosis, pneumonia, and pulmonary edema are incorrectly classified as COVID-19. This is because other normal and abnormal cases are not seen in the training process. Such a scenario is evaluated to see the performance of the trained model when it is needed to deal with unseen diseases in real usage.

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