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Deep learning model for thorax diseases detection

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ABSTRACT

Despite the availability of radiology devices in some health care centers, thorax diseases are considered as one of the most common health problems, especially in rural areas. By exploiting the power of the Internet of things and specific platforms to analyze a large volume of medical data, the health of a patient could be improved earlier. In this paper, the proposed model is based on pre-trained ResNet-50 for diagnosing thorax diseases. Chest x-ray images are cropped to extract the rib cage part from the chest radiographs. ResNet-50 was re-train on Chest x-ray14 dataset where a chest radiograph images are inserted into the model to determine if the person is healthy or not. In the case of an unhealthy patient, the model can classify the disease into one of the fourteen chest diseases. The results show the ability of ResNet-50 in achieving impressive performance in classifying thorax diseases.

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1. INTRODUCTION

Chest diseases are one of the most important health problems people experience. More than 1 million adults with pneumonia are hospitalized, with about 50,000 dying each year in the United States alone [1, 2]. Chest x-ray images are the most common tool used to diagnose chest diseases, since their devices, in addition to making the patient exposed to little radiation, are also fairly cheap [3]. Depending on world health organization estimates, about two-thirds of the planet's population suffers from a lack of access to radiation diagnosis [4]. Even with the availability of the necessary equipment for radiography, the experts who are able to interpret the x-rays are few, especially in rural areas, leading to an increase in the mortality rate of treatable diseases in many countries [5]. So early diagnosis and treatment should be available to prevent complications of pneumonia that may lead to death.

In recent years, deep learning models have made significant advances in many digital image applications [6-9], which have included faster and earlier detection of any diseases with the help of medical image classification and detection. According to the success of deep learning, many researchers have sought to benefit from deep neural networks (DNNs) for diagnosing many diseases, including thorax diseases on chest radiography, where numerous reports have been published confirming high accuracy of deep learning in diseases diagnosis. Much research has been done using deep learning methods to detect abnormal objects in medical images [10-15].

For instance, in [16], digital image processing techniques are used to develop a simple preprocessing pipeline and expert radiologist advice. Three neural network architectures: GoogLeNet, InceptionNet, and

ResNet are created. These models have efficiently proven in classification tasks which are applied on chest x-ray images. In [17] a unified convolutional neural network (CNN) framework was proposed using weakly-supervised multi-label classification, taking into account that pooling strategies are different as well as various CNN's multi-label losses. Also, in [18] the CheXNet model, which is a model of deep learning, has been proposed for the detection of pneumonia where the area was diagnosed with the disease is identified in the image and used dense connections [19] and batch normalization [20] for making the optimization more possibility to execution for such a model. According to the results they reported, CheXNet has the capability to detect pneumonia at a level equal to or greater than that of radiologists. In [21] backpropagation neural network (BPNN), CNN plus competitive neural network (CPNN) were tested for the most common disease classification in Chest x-ray. The recognition rates were high and performance was good where the input image has a size of 32×32 pixels according to the results that they presented. CPNN and BPNN achieved less generalization power than that achieved by CNN. In [22] ChestNet is proposed to address the diagnosis of thorax diseases on chest radiography and was compared with three deep learning models on Chest x-ray14 dataset [17] using the official patient-wise split. According to the results presented the results were higher than those achieved by previous methods.

In all of the above, a number of methods were offered to diagnose chest diseases with the help of computer-aided diagnosis. However, the problem of increasing the success rate of diagnosis of diseases remains one of the most important tasks to complete the diagnosis process and make it more efficient. So the model was proposed to diagnose the chest condition based on radiography. The diagnosis determines whether the person is normal (no finding) or abnormal. In case of abnormal, the model can detect fourteen types of chest diseases. One of the deep learning models, RestNet-50, has been suggested for its high ability to diagnose chest diseases on X-rays, as well as high potential to avoid many of the problems that the network may encounter when they become deeper. The proposed ResNet-50 model was evaluated against four deep learning models on Chest x-ray14 dataset. The block diagram of the proposed model is shown in Figure 1. The remaining of this paper is structured as follows: in section 2, the proposed model ResNet-50 and its architectures are described. The dataset used in the experimentation is described in section 3 along with its preprocessing. Finally, the results are presented in section 4 with corresponding discussions followed by the conclusions in section 5.

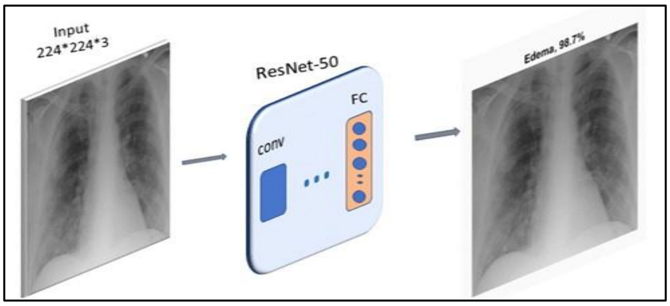


Figure 1. Illustration of chest image analysis with ResNet-50 model

2. PROPOSED MODEL

In this work, the proposed model is divided into three steps: preprocessing, ResNet-50, disease diagnosis as shown in Figure 2. In the preprocessing step, there are three blocks: first, to obtain more accurate and reliable data from Chest x-ray image, the rib cage area is cut to retain on it and leave the remaining areas in the image. This cropping process makes the training data more useful and thus increases the accuracy of the results and reduces the time of training. Secondly, the images are converted to RGB. Thirdly, the images come with different sizes. Therefore, the images must be unified within a certain size as required by the proposed network. During the training process, some details may be forgotten in the images, so the images are repeated to make the network remember the most details. In addition, this process increases network resolution. In ResNet-50, the earlier layers are freeze, while the fully connected is replaced according to requirements of the work. The last decision appears to determine the case of the chest is taken in the last step.

2.1. ResNet-50

The architecture of the ResNet-50 deep learning models is shown in Figure 3. It consists of 50 layers. Unlike other DNN, ResNet-50 model is characterized by its ability to avoid some of the problems confront the network when increasing its layers. One of these problems is when the number of layers increases to more than 25 layers starting with the problem of vanishing gradients, which is formed when the gradient is very small then the weights will not be change effectively and it may cause the neuronal network to stop completely for future training [23]. So, this model has been utilized in this work due to its high ability to avoid many problems as well as its efficient performance in the diagnosis of chest diseases.

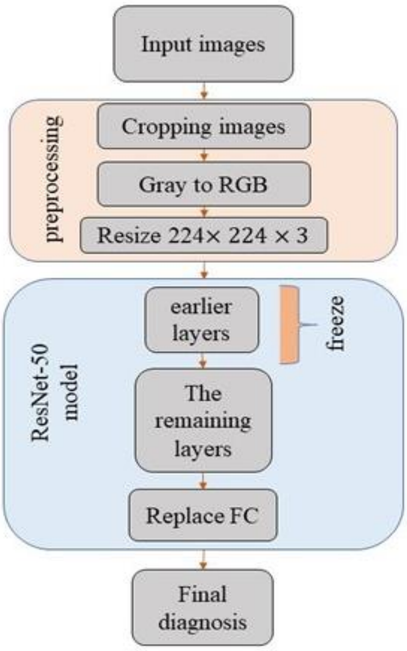


Figure 2. Proposed model block diagram

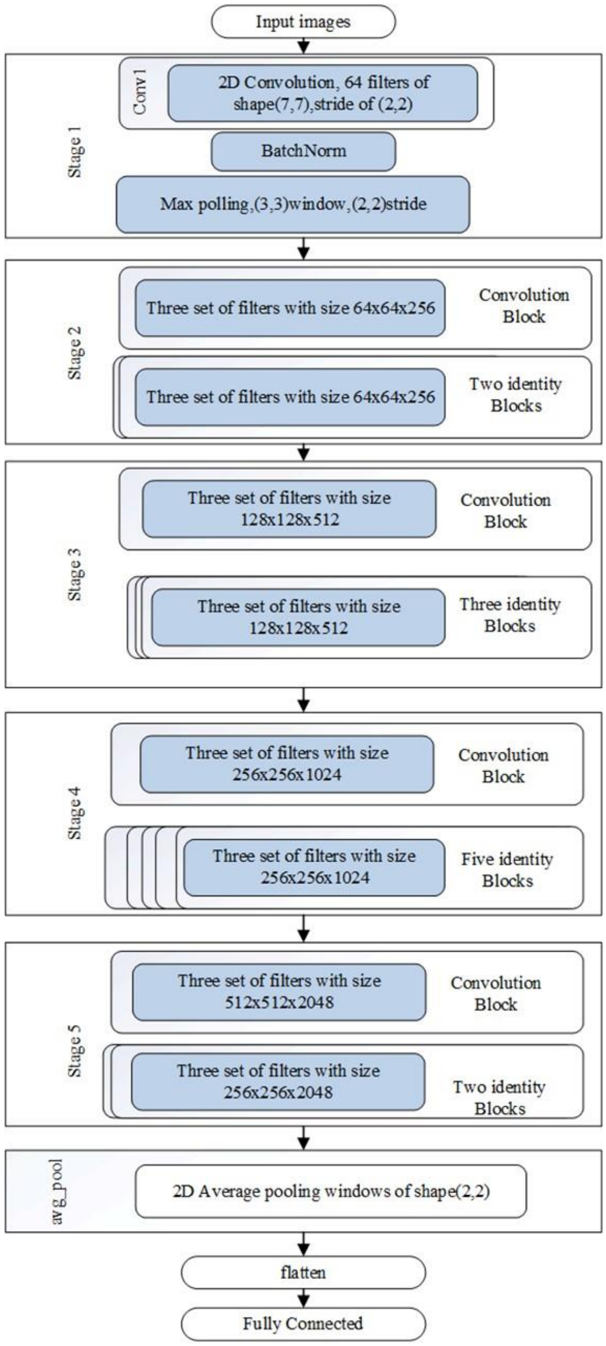


Figure 3. Architecture of ResNet-50 model

In this paper, two important strategies for ResNet-50 is investigated. First, the model parameters with random values were initialized, so the model is trained from the beginning. In the second strategy, the weights of the model are initialized from pre-trained. In the proposed model, the first layer requires input images of size 224×224×3, where 3 is the number of colors (ResNet-50 were designed in order to process the RGB images depending on the ImageNet [24] dataset), so gray images converted to color images. Then color images are passed to the proposed model as the initial layers where their weights are frozen by making learning rates equal to zero. Various levels of the features of Chest x-ray images are extracted in the first convolutional layer and this is shown in Figure 4 where the learned filters are shown at convolution layer. To retrain the model for new classification tasks, where the last full connection has been removed, which content 1000 classes and replaced by fully connected with fifteen classes. During training, at the frozen layers, the parameters do not update. The speed of model training is greatly increased when the weights of the initial layers are frozen as a result of counting the gradients of the layers that have been frozen.

ResNet-50 contains two blocks, Convolutional block and Identity block depending on the dimensions of the input/output, whether similar or different. Identity block is used when the dimensions are similar, while the convolutional block is used when the dimensions are different. Figure 5 shows the architecture of each of convolutional block and identity block. In the next section, the dataset used in this work is described.

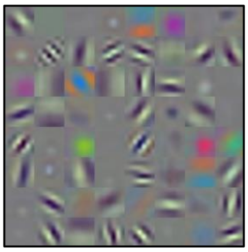
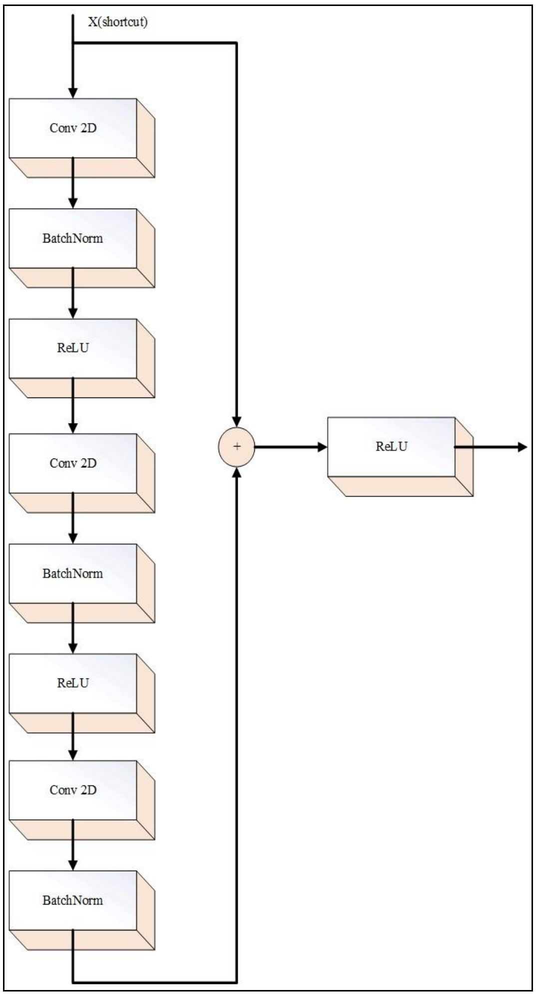
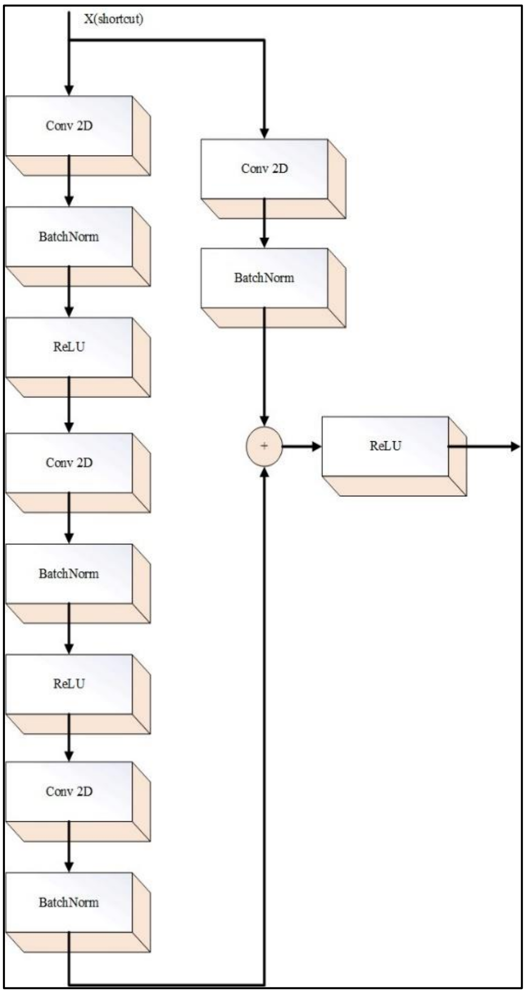


Figure 4. Trained convolutional filters in the first layer



(a)



(b)

Figure 5. Types of blocks in ResNet model: (a) identity block, (b) convolutional block

3. DATASET

In this work, the publicly available radiographic dataset, Chest X-ray 14 released by Wang et al. [17] was used. The dataset includes 3182 x-ray images, some examples of this dataset are shown in Figure 6. This dataset has fifteen labels consisting of Normal label and 14 disease labels include: effusion, consolidation, edema, cardiomegaly, atelectasis, emphysema, fibrosis, nodule, hernia mass, infiltration, pneumothorax, pleural thickening, and pneumonia. The labels of our dataset are clearly illustrated in Figure 7, which displays the total number of images. For the detection task, the dataset is randomly split into testing 15% (476 images), validation 15% (480 images), and training 70% (2226 images). The images were saved in PNG format. The digitized images were cropping and duplicating.

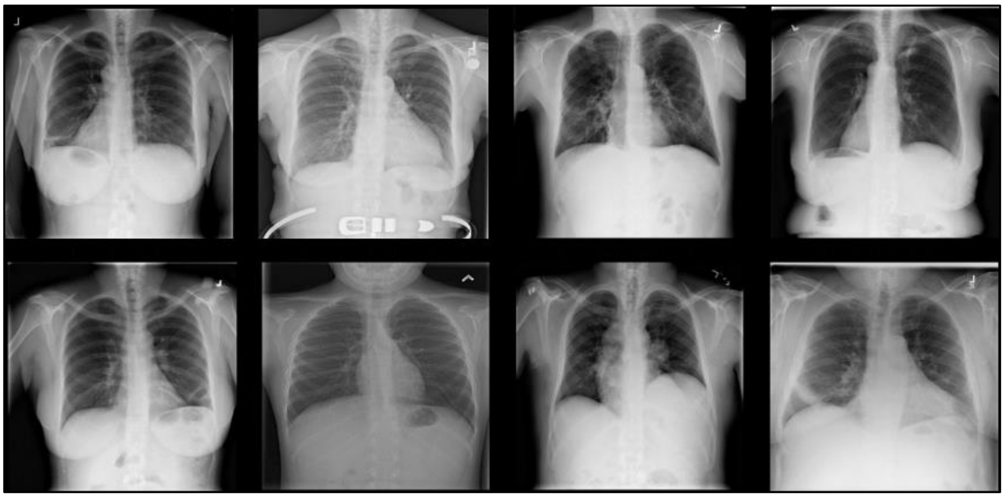


Figure 6. Eight examples from chest x-ray 14 dataset, where the chest x-ray 14 includes 112, 120 images from 30,805 patients

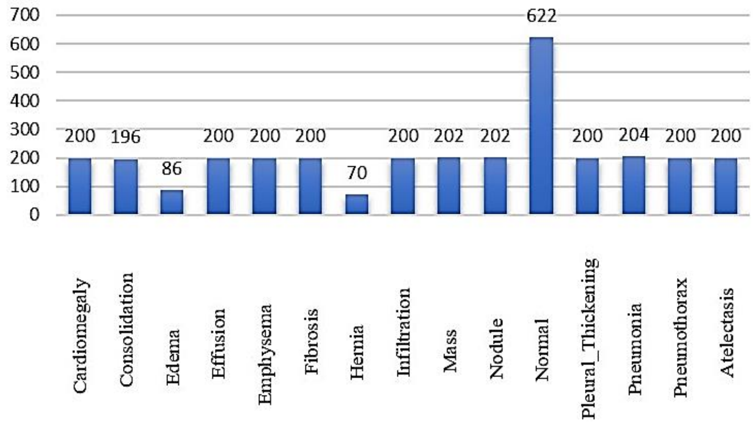


Figure 7. Number of images in each label

4. RESNET-50 MODEL RESULTS

The results obtained from the proposed model were presented in this section. The model is implemented in Matlab 2018a using Deep Learning Toolbox for ResNet-50 Network [6], working on a computer with 8 GB memory and Intel(R) Core (TM) i7-8550U CPU @ 1.80GHz. The training parameters are set as follows: the mini-batch stochastic gradient descent algorithm has been adopted where the learning rate to 0.0001, and the batch size is 10, maximum iteration number is 13320 and at the layer of fully connected that the factor of bias learn rate is 10 and the weight of factor of learning rate is 10.

The proposed model achieved very high results in reading radiography and chest diagnosis where the area under curve (AUC) reached to 0.9261. In Figure 8, the example shows the end result of how the diagnosis is made through the proposed model. The patient was diagnosed with the Edema. Table 1 shows the recognition rates obtained for the proposed network where it showed that the accuracy using the proposed network has 93.03% for training and 94.49% for testing. Also, the overall performance for training time, amount of data, and the recognition rate is described in Table 2. The averaged time of classification an image using the trained network was 0.3 second per image. Thus providing less time and less effort to obtain a diagnosis. The total training time to the proposed network took about 29-30 hours.

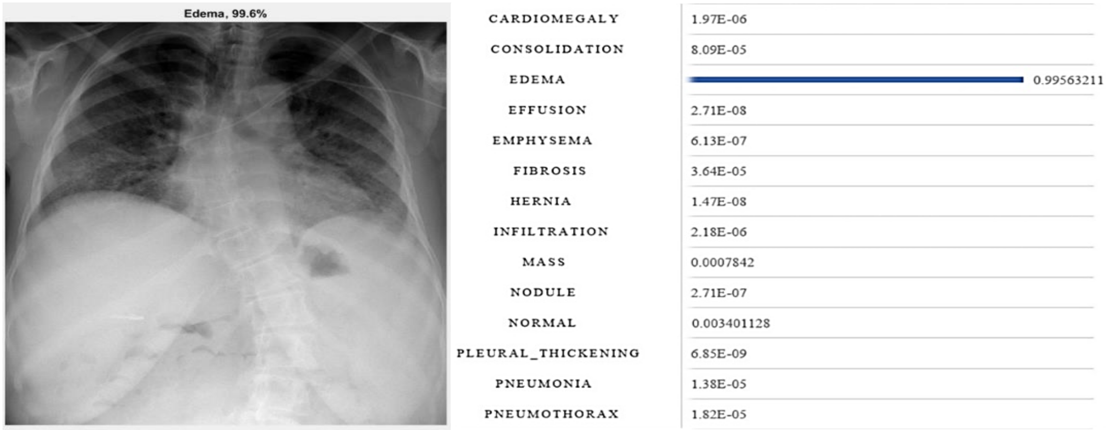


Figure 8. Chest x-rays image with its diagnosis and the classes probabilities

Table 1. Performance rates for ResNet-50 on training, validation, testing, and overall data

Network model	Data for training (70%)	Data for validation (15%)	Data for testing (15%)	Overall data (100%)
ResNet-50	93.03%	93.42%	94.49%	93.18%

Table 2. Performance rates for ResNet-50 of the proposed network

Network model	Training time	Recognition rate	Overall data	Maximum number of iterations
ResNet-50	1055 min	93.18%	3182 images	13320

The model achieved good diagnostic results for all groups, with the highest accuracy being 96.5% of the edema disease category, which 86 images and less accurate being 85.71% of the hernia disease category, which 70 images as shown in Figure 9. In Table 3, the proposed model was compared with three deep learning models where the per-class AUC obtained by applying the test dataset to those models. The proposed model achieved the highest rate for most of the classes as shown by the results. Among the models that were trained on the Chest x-ray14 dataset, our model achieved the highest accuracy ratios for most cases. The results showed that the proposed model with the deeper net had a lower error rate than those with lower layer's depth. The results show that increasing network depth increases the network's ability to classify. The proposed model achieved a rating accuracy of 92.71%, while the results of previous networks were 84.1378%, 80.2714% and 73.8142%. Despite the depth of the model, the complexity is still low. An image was taken for each case (15 different images) and then was presented to the proposed models to determine the appropriate diagnosis where the results are as shown in Figure 10.

Table 3. Comparison AUC on chest x-ray 14

Chest case	wang et al. [18]	Yea et al. [25]	Rajpurkar et al. [19]	Proposed network
Atelectasis	71.6%	77.2%	80.94%	93.5%
Cardiomegaly	80.7%	90.4%	92.48%	94%
Consolidation	70.8%	78.8%	79.01%	91.33%
Effusion	78.4%	85.9%	86.38%	91%
Emphysema	81.5%	82.9%	93.71%	94.5%
Fibrosis	76.9%	76.7%	80.47%	96.5%
Infiltration	60.9%	69.5%	73.45%	88.5%
Mass	70.6%	79.2%	86.76%	94.06%
Nodule	67.1%	71. 7%	78.02%	91.58%
Pneumonia	63.3%	71.3%	76.8%	92.16%
Pneumothorax	80.6%	84.1%	88.87%	93.5%
Edema	83.5%	88.2%	88.78%	96.51%
Pleural Thickening	70.8%	76.5%	80.62%	91.5%
Hernia	76.7%	91.4%	91.64%	85.71%
Normal	-	-	-	96.3%
Average	73.8142%	80.2714%	84.1378%	92.71%

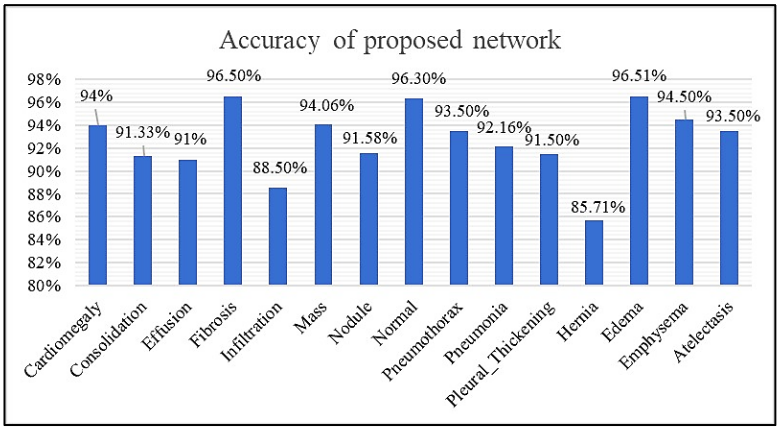


Figure 9. Performance rates for fifteen cases in classification

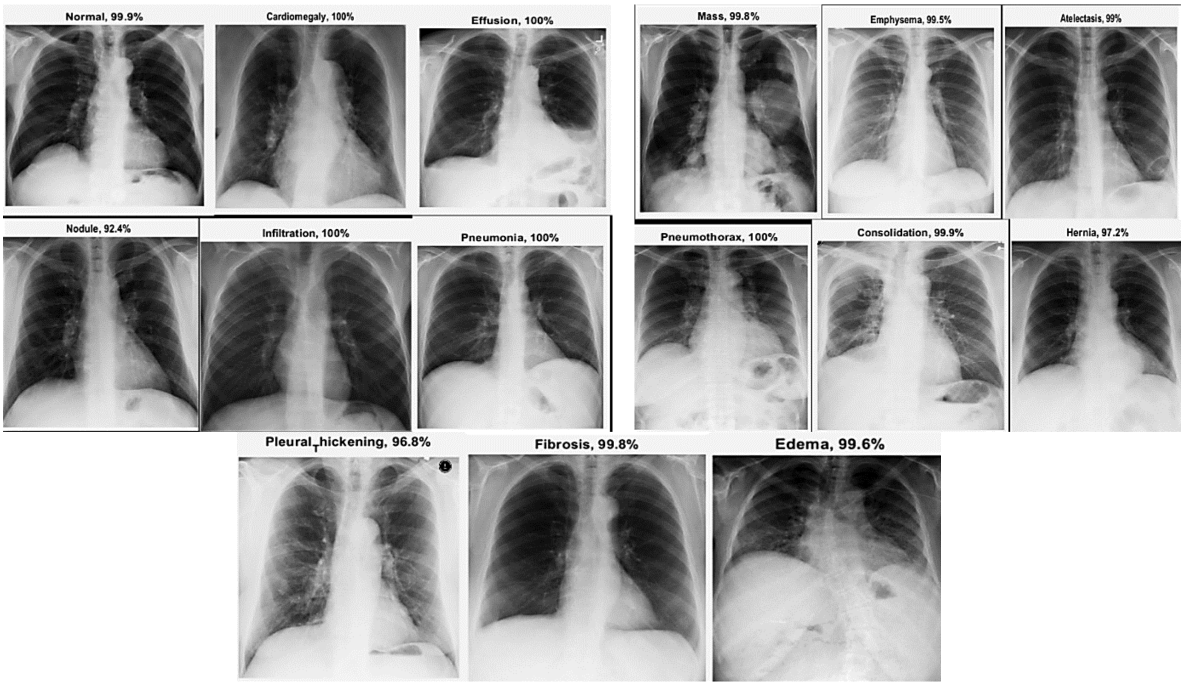


Figure 10. Some results of diagnostic detection in radiography images. An example of each classification was taken

5. CONCLUSION

In this paper, a proposed chest diagnose model was applied to chest radiographs to diagnose 15 cases (14 chest diseases and 1 normal condition), based on ResNet-50 re-training. It achieved high efficiency in the diagnosis of chest radiography using the deep learning model with an AUC rate for all classes of 0.9261. This model was then compared to three models of deep learning used Chest X-ray 14 data set where it was superior. It is hoped that this model will improve the progress of health care and increase access to the medical experience throughout the world when access to skilled radiologists is limited. In our future work, work should be done to increase control of ResNet-50 using actual x-ray data, where ResNet-50 can be significantly increased by this configuration. The results showed that the use of deep learning methods is useful for detecting x-ray diseases on the chest.

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