Identifying the Presence of Covid-19 on X-ray Medical Images Using a Neural Network

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Abstract. **In this paper, we propose a neural network implementation and its improvements for identifying the presence of covid-19 on X-ray medical images using a neural network.**

Keywords: **covid-19, covid, neural network, convolutional neural network X-ray medical images**

I. Introduction

Now, there is a big problem in the world with the workload of doctors due to the Covid-19 pandemic. Viral pneumonia is a common complication of influenza-like illnesses and is a complication of SARS-COV-2[1].Viral pneumonia may clear up on its own; however, when severe, it can be life-threatening. Viruses are generally not as common a cause of CAP as some bacteria. However, as well as being a primary pathogen, viruses can be a co-pathogen with bacteria, particularly in those with severe illness requiring admission to ICU and in ventilator-associated pneumonia.A huge number of people need medical care, so the problem of unloading medical personnel using machine learning technologies is urgent. This article explores the possibility of classifying X-ray images using machine learning and deep learning approaches [2]. Since the massive victory of deep convolutional neural network in the 2012 ImageNet competition, the field of deep learning has experienced a huge increase in popularity, and a significant number of different neural network architectures have emerged [3]. For image processing, convolutional neural networks are used, as a rule since they are able to use the local relationship of image pixels. The learning time of such a network becomes a common problem. This article will provide an example of a neural network designed to detect the signs of Covid-19 on chest X-rays and will look at an attempt to shorten the training time of this neural network. X-rays of the chest will be fed to the input of the neural network, an example of such images of a person without Covid-19 and a patient with a diagnosis of Covid-19 can be seen in Fig. 1 [3].

II. Dataset Properties

In this research we use a public open dataset of chest X-ray and CT images of patients which are positive or suspected of COVID-19 or other viral and bacterial pneumonias (MERS, SARS, and ARDS.) [4]. Data will be collected from public sources as well as through indirect collection from hospitals and physicians. All images and data will be released publicly in this GitHub repo (https://github. com/ieee8023/covid-chestxray-dataset). Dataset is represented as collection X-Ray images. Those images have size 255x255.Every image is supported by metadata about patients including viral, bacterial, fungal, lipoid, aspiration, sex, age, finding, RT_PCR_positive, survival, intubated, intubation present, went_icu and other.

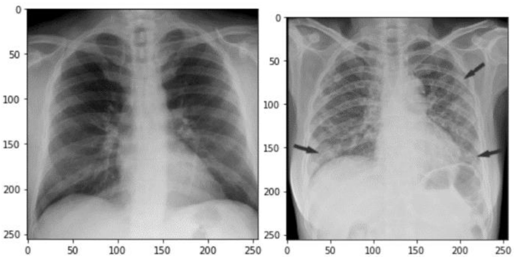

Fig. 1. X-ray of a patient with coronavirus (right) and without (left)

We try modify this information by definition of regions with condensed information using bounding box like as Fig. 2.

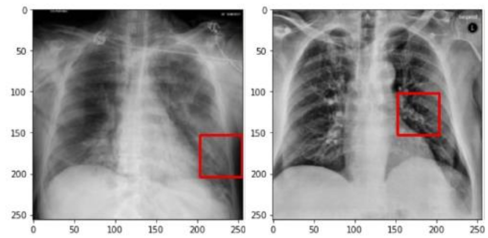

Fig. 2. X-ray images with marked pathology by bounding box

Also, this dataset is supported by information map with features positions (Fig. 3).

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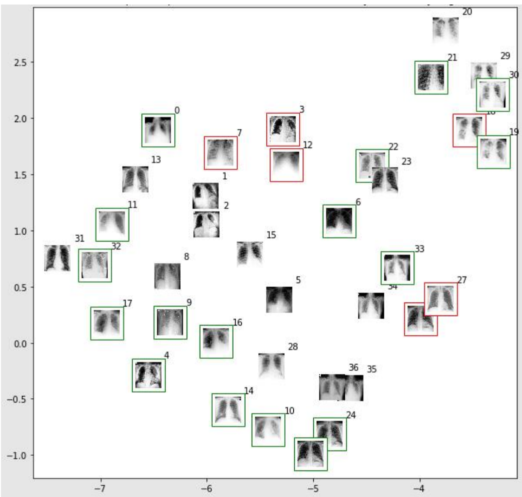

Fig. 3. The map of feature space of pretrained network on COVID-19 X-ray, where true case is marked as green and false case is marked as red

III. NEURAL NETWORK

As basic methods we try to use fully convolutional network for semantic segmentation. It allows to compared with classification and detection tasks, segmentation is a much more difficult task and spend image classification like as [5].

For object detection is used classification within an image with bounding boxes of pathology regions. That means we also need to know the class, position and size of each object. Classify the pathology class for each pixel within an image. That means there is a label for each pixel.

To avoid the “vanishing gradient” problem that sometimes occurs with the usage of the popular ReLU activation function, the ELU activation function has been used instead. Fig. 5 shows the difference between ReLU and ELU, Fig. 6 shows the architecture of the used neural network:

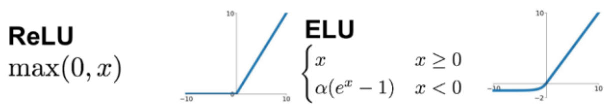

Fig. 5. The difference between ReLU and ELU

IV. IMPROVEMENTS

One of the possible and the most basic simplification of the model is to reduce the dimension of the input data by converting the image to black and white instead of the usual network by three times. It is important to understand that this decreases the amount of incoming data only for the first convolutional layer, since the number of output channels is specified by another parameter.

Let's check the difference in training time for this network [3] with the number of input channels equal to 1 and 3. With three input channels, the neural network has been training for 5 minutes 55 seconds, and with one, the neural network has been training for 5 minutes 33 seconds. The training was carried out on an Nvidia 1650 TI GPU. An increase in the number of input layers from 1 to 3 increases the training time by almost 7% and does not give a noticeable increase in quality, which indicates the usefulness of the proposed approach.

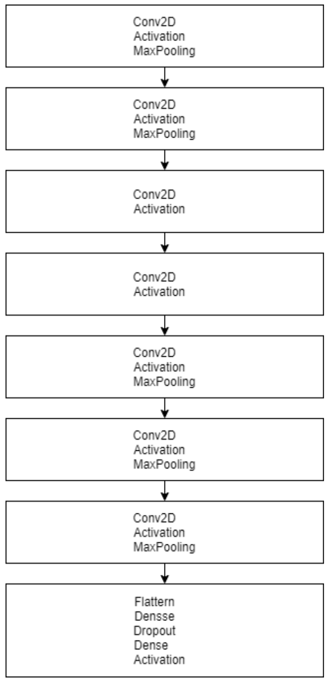

Fig. 6. Architecture of an applied neural network

V. QUALITY METRICS & RESULTS

In diagnostic tasks, positive examples are more important than negative ones, therefore, priority was given to positive examples. The confusion matrix on the test dataset is on Fig. 7:

	precision	recall	f1-score	suppor
False	0.66	0.65	0.66	6
True	0.83	0.84	0.83	12

Fig. 7. Confusion matrix

The discrete ROC curves of these approaches are plotted in Fig. 8. From this picture, it is clearly that proposed model of neural network consistently achieves the impressive performance in terms of the discrete ROC curve.

The Fig. 9 shows an example of an input image and a map of the cumulative intensity of convolutions after layer 19 for this image.

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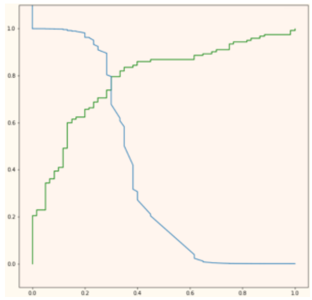

Fig. 8. Architecture of an applied neural network

The black areas correspond to the areas that contribute the least to the result [3].

After smoothing the weighted sum of the image shown in the Fig.6, the following picture (Fig. 9) is obtained. Some of the brighter areas are located in other spots than the location with the Covid-19 signs. This is due to the presence of colors with greater brightness and to the fact that this is not the last layer of the network, so there is reason to suppose that the neural network has learned to process such structures Fig. 10.

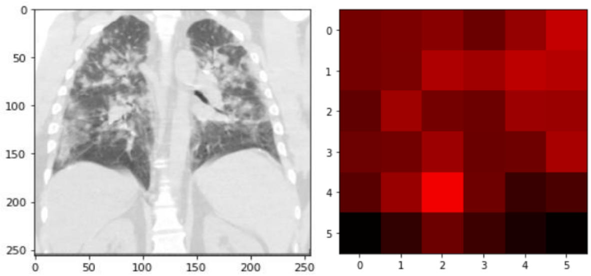

Fig. 9. An example of affected lungs (left), a brightness map at the output after layer 19 (right)

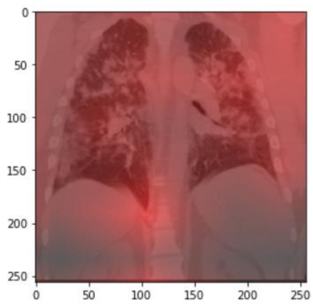

Fig. 10. Smoothed luma map after layer 19

VI. Conclusion and Further Research

The augmentation is helpful in a small database. However, it is also been found that augmenting a large number of images from a small set of images influences model accuracy because of the addition of noise during model training. On the other hand, a very small number of images did not produce the best result for any model due to the under fitting problems in the pre-trained model. The dataset is downloaded from an open-source online repository. The promising results obtained using CNN models suggest that Chest X-Ray can be useful for early detection of the Coronavirus as compared to the time-consuming pathological test or costly CT-Scan [6].

It is possible to use a more complex neural network structure. There are 2 options here: train the neural network from scratch or try to fine-tune some already existing model, for example, YOLOv4 [7], since it shows impressive results in other tasks. The variant with training a large neural network from scratch takes a lot of time and, probably, a significant increase in the training sample, to avoid memorizing the training sample by the neural network of many training parameters and an insufficient volume of the training sample.

To build a brightness map, you can use a weighted convolution value that will consider the weight in fully connected layers. This will allow to determine which areas of the original image make the greatest contribution more accurately to the result.

The question of the need to use data augmentation remains open, there are reasons that there is no sense in this: the X-ray images are similar to each other, since people are in the same postures during the X-ray examination. Also, all images are usually taken from the same distance and angle.

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