Youngjae (Bush) Moon and Jeongmin Yoo
Group Name: Daimler AG
Professor Pravin Pawar
CSE 351 Course Project Milestone 3
June 14th, 2020

Final Project Report

1. About Machine learning techniques

Most importantly, we have used a convolutional neural network (CNN) to solve the problem at hand. The CNN assumes that the input is an image. It is used a lot in areas where object recognition and computer vision are needed, such as autonomous driving and face recognition. The convolutional neural network is effective for image processing and pattern recognition due to its high accuracy.

The CNNs are composed of four main types of layers. The first layer is a convolution layer which is for discovering and locating the existence of smaller patterns in a larger image. The second layer is a pooling layer which is for reducing the size of the input image without losing much information so that faster computation can be made. The third layer is the rectified linear unit layer which is for mapping an input signal to an output signal through compressing the input into a smaller range so that redundant information can be eliminated and non-linearity can be added. Here Rectified Linear Unit (ReLU) is a type of activation function which converts all the negative values into zeros while maintaining all the positive values. The last layer is fully connected to build some final topology.

For the segmentation network, we have employed Densely Connected Convolutional Network (DenseNet). There are four advantages that DenseNets have. As Chablani stated, "they alleviate the vanishing-gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the number of parameters." Since the purpose of the segmentation network is to extract lung and heart contour from chest X-ray (CXR) images, we decided to use DenseNet for semantic segmentation.

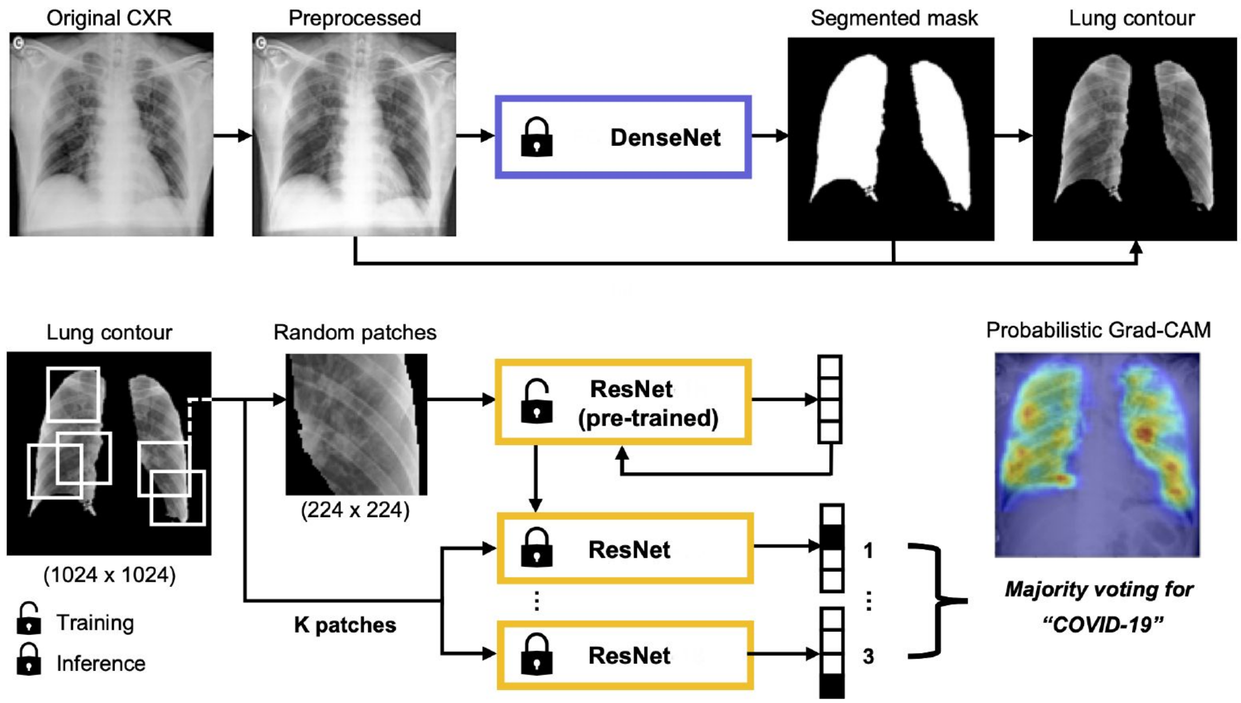
There are several advantages that DenseNets have compared to typical CNNs. As Ruiz has stated, "[t]he problems arise with CNNs when they go deeper. This is because the path for information from the input layer until the output layer (and for the gradient in the opposite direction) becomes so big, that they can get vanished before reaching the other side." By contrast, "DenseNets simplify the connectivity pattern between layers introduced in other architectures" such as highway networks, residual networks, and fractal networks (Ruiz).

Last but not least, we have employed a residual neural network (ResNet) for our classification network (a network which classifies CXR images according to the disease for two main reasons. First and foremost, through the employment of ResNet, overfitting can be minimised. Overfitting can occur when using an excessively complicated model for a small size of data. We believe our dataset is not large enough to employ more complex models since we have limited our dataset to Kaggle's dataset. Moreover, transfer learning with pre-trained weights from ImageNet is possible through the employment of ResNet. In this way, we can reduce the problems created by using a small training dataset for this project. According to Oh et al., "these strategies make the training stable even when the dataset size is small" (3).

All of these neural networks are examples of deep neural networks (DNN) as they consist of multiple layers between the input layer and the output layer.

2. Applying machine learning techniques

The following diagram shows the overall architecture of our proposed model for this project. Note that we have preprocessed the images while we were doing milestone 2. We will input our resized images to DenseNet and then DenseNet will output the corresponding Lung contour. Then, we will train ResNet the random patches that COVID-19 pneumonia patients and Normal pneumonia patients have and thereby build an AI program that classifies COVID-19 pneumonia patients from other people.



3. Presenting your results

Present your results in a tabular and graphical form. You can write scripts to create graphs or use any of the available tools.

4. Conclusion

X-ray testing method is less trustworthy than RT-PCR tests despite X-ray scanners' various advantages compared to RT-PCR kits. This is because X-ray testing methods is not based upon the causation but instead correlation. In other words, it is only based upon the tendency that COVID-19 pneumonia patients have for their chest X-ray (CXR) scans. There is no scientific proof that these signs of infection are only caused by COVID-19. By contrast, RT-PCR tests can effectively classify COVID-19 patients by identifying the DNA of COVID-19.

We did not achieve the first project objective as the X-ray testing method is not effective to distinguish between COVID-19 pneumonia patients and other viral pneumonia patients. This failure is mainly due to the fact that the cardiothoracic ratio of COVID-19 pneumonia patients and other viral pneumonia patients are similar. Thus, other patients such as tuberculosis patients, bacterial pneumonia patients, lung cancer patients can also be infected by COVID-19 (not mutually exclusive). In this case, X-ray testing methods cannot show that these patients have been infected by two or more diseases.

We did not achieve the second project objective since X-ray testing method is not effective to identify asymptomatic patients and severely ill patients. For asymptomatic patients, this is mainly due to the fact that COVID-19 patients who do not have a certain number of viruses in their lungs cannot be identified as a patient at all. Thus, COVID-19 patients who are severely ill because there is an excessive number of COVID-19 in their lungs can be misclassified to other diseases.

In these instances, though, as stated by Oh et al., "the current diagnostic performance with CXR is not sufficient for routine clinical use, so the need of artificial intelligence to improve [the] diagnostic performance of CXR is increasing." Due to the limited number of RT-PCR kits in the world, CXR can be used initially to differentiate the people into the people who will likely obtain positive results in the RT-PCR tests, and the people who will not. In this way, with the adoption of artificial intelligence technologies, people who need to take RT-PCR tests can have different priority in the future.

Last but not least, we have achieved our third project objective by only using the dataset from Kaggle. In this instance, though, we have realised the need to find more X-ray datasets from lung cancer patients, tuberculosis patients, bacterial pneumonia patients, etc for more precise and accurate classification.

5. Future work

In the future, we will instead develop a testing method to classify COVID-19 patients through CT scanning, as CT scans show more detailed pictures of the patients than the X-ray images. We can go through a similar process for classifying COVID-19 and other patients using CT scans, though we need more dataset for CT scans. Currently, there is not enough dataset available for the classification using CT scans.

Thus, we will collect more dataset from various types of patients such as tuberculosis patients, lung cancer patients and bacterial pneumonia patients. In this way, the precision and accuracy of the artificial intelligence program (AI) can be improved. Although other types of patients can be also infected by COVID-19, the classification cannot be effectively made through the use of AI as the model is based upon the distribution and the opacity of the lesions.

We also learnt that artificial intelligence programmes can use methods that have not been employed by human radiologists to automate their work. For instance, while humans are not good at identifying various types of patients through the intensity of each X-ray image, computers are good at this method. Radiologists typically use the distribution of lesions to label various types of patients, whereas computers are less suitable at employing this method (computers need more training than human radiologists). Hence the automation of radiologists' jobs through AI and big data will be achieved through training computers in a different manner compared to training humans to become radiologists.

Works cited

Chablani, Manish. “DenseNet.” *Towards Data Science*, 25 Aug. 2017, towardsdatascience.com/densenet-2810936aeebb. Accessed 15 June. 2020.

Oh, Yujin, et al. “Deep Learning COVID-19 Features on CXR Using Limited Training Data Sets.” *IEEE Transactions on Medical Imaging*, 8 May. 2020, pp. 1–1, doi:10.1109/TMI.2020.2993291.

Ruiz, Pablo. "Understanding And Visualizing Densenets". *Towards Data Science*, 2020, https://towardsdatascience.com/understanding-and-visualizing-densenets-7f688092391a. Accessed 15 June. 2020.