The application of deep learning to diagnose COVID-19 using Chest X-Ray image

Group 5 DlAlot

Li Ju and Xinran Cui  
Statistics department  
University of Illinois Urbana-Champaign,

Champaign, USA,

{liju2, xinranc3}@illinois.edu

*Abstract*—This thesis describes the design progress of a deep learning project for diagnosis of COVID-19, which applied CNN to classify Chest X-Ray image.

Keywords—CNN, VGG-16, COVID-19, Image Classification

# Introduction

For the group project, we are planning to predict the diagnosis result of Covid using X-ray images. At this time, it is vital to have an effective way to detect Covid precisely. Also, we are interested in implementing image detection techniques and decreasing the false negative error specifically. Our neural network's input is the image data of the chest x-ray image, and the output will be the result of the covid diagnosis. The specific deep learning algorithm for build networks is CNN and we plan to improve the performance of the model using normalization and regularization.

# Related Work

Ismael and Şengür(2021) ->[1] discussed the application of CNN to classify image in one of their papers, which mainly uses deep learning based methods, fine-tuning of pretrained convolutional neural networks (CNN), and end-to-end training of a developed CNN model to classify X-ray images to positive cases and negative. More specifically, for both deep feature extraction and fine-tuning procedures, the ResNet18, ResNet50, ResNet101, VGG16, and VGG19 models are used. For the training of the deep features, SVM classifier is used with various kernel functions -- Linear, Quadratic, Cubic, and Gaussian. A 21-layered new CNN model was also proposed and trained end-to-end. The proposed network model starts with an input layer, then there are five convolutions layers, five ReLU layers, and five batch normalization layers, respectively. Two pooling layers are used after the first and second ReLU layers, respectively. A fully-connected layer, softmax layer, and classification layer are also used at the end of the model. Dong, Pan, Zhang, and Xu (2017) -> [2] constructed a vast dataset containing chest X-ray images to which they applied deep CNN models for binary and multilevel classifications. Transfer learning with pretrained AlexNet, ResNet, and VGG16 models were used with the constructed dataset. While an 82.2% accuracy score was reported for the binary classification, over 90% accuracy scores were reported for the other classification tasks. Minaee, et.al (2020) ->[3], using a dataset of 5, 000 Chest X-rays from the publicly available datasets, they uses transfer learning techniques to train four popular convolutional neural networks, including ResNet18, ResNet50, SqueezeNet, and DenseNet-121, to identify COVID-19 disease in the analyzed chest X-ray images. To deal with the scarcity of the COVID images, the paper implements data augmentation to create transformed versions of COVID-19 images to amplify the amount of data by a factor of 5. Furthermore, it fine-tunes the last layer of the pre-trained version of these models on Ima- geNet to have less labeled samples from each class. The sensitivity rate of 98% ( ± 3%) and a specificity rate of around 90% are reported as a result. Tartaglione et.al (2020) ->[4] mentioned the possibility of using deep learning to make early diagnosis with some small datasets. Our project also applied CNN algorithms to do the image classification as Tartaglione and his colleagues did. But they had more complicated data pre-processing than ours - they made histogram generalization and lung segmentation to Chest-Xray graphs before putting them into the training process while our project directly put the original graphs into training. Another paper (Jadon, 2021) ->[5] also mentions the problem of scarce medical data for modelling covid-test results via Chest-X Ray graphs. Jadon also mentioned the base CNN (Cov2d+Maxpool+Flatten+Dense) is a key foundation for using deep learning to obtain early diagnosis results for covid. But he went deeper when discussing the application of transferring learning in covid test - VGG-16 architecture trained on Image-Net is an optimized neural network for image classification. Wang, et al.(2020) -> [7] explained how a tailored deep convolutional neural network works for detecting COVID-19 using Chest X-Ray images. Different from our simple CNN architecture, the COVID-Net had high architectural diversity and selective long-range connectivity, and it highly used projection-expansion-projection design, which is specifically beneficial for COVID-19 detection using Chest X-Ray images. Basu, et.al(2020) -> [8] proposed a novel concept called domain extension transfer learning (DETL) when applying deep learning techniques to COVID-19 detection. The scholars used a similar dataset as the one we used, both of which have 4 categories of Chest X-ray images. What their study is different from ours is that they used transfer learning to tune a CNN pre-trained on a large amount of images, which could avoid a time-consuming training process. Narin, Kaya and Pamuk(2020) -> [9] has proposed automatic detection of COVID-19 using deep learning techniques and Chest X-Ray images. Different from our work, they parallelly used five pre-trained models, ResNet50, InceptionV3, ResNet101, Inception-ResNetV2 and ResNet152 and then specified a pooling layer and fully connected layers based on the context. The reason they used pre-trained models is that pre-trained models could help to improve accuracy of the model trained even with a small dataset. Zhang, Xie, Li, Shen and Xia (2020) -> [10] developed a new deep anomaly detection model for fast, reliable screening. The model is composed of three components -- a backbone network which is a 18-layer residual convolutional neural network pretrained on the ImageNet, a classification head with a stride of 2 and a multilayer perception, which contains a 100-neuron hidden layer, a one-neuron output layer, and the sigmoid activation. As a result, they achieved the sensitivity of 90.70% and specificity of 83.30% on a large-scale CT dataset. Jain, Mittal, Thakur and Mittal (2020) -> [11] proposed a method consisting four stages: (i) image preprocessing, (ii) data augmen- tation, (iii) training of deep learning ResNet50 network to differentiate viral induced pneumonia, bacterial induced pneumonia and normal cases (iv) training ResNet-101 network to detect the presence of COVID-19 from positive viral induced pneumonia cases using X-ray images. As a result, the paper achieved a High classification accuracy as 97.77%, recall as 97.14% and precision as 97.14%.

# Data

The dataset is sourced from Kaggle [6]. The dataset contains chest X-ray images for COVID-19 positive cases along with Normal and Viral Pneumonia images. The dataset is released in stages. In the first release, there are 219 COVID-19, 1341 normal and 1,345 viral pneumonia chest X-ray (CXR) images. In the first update, the dataset increased the COVID-19 class to 1,200 CXR images. In the 2nd update, it increased the database to 3,616 COVID-19 positive cases along with 10,192 Normal, 6,012 Lung Opacity (Non-COVID lung infection) and 1,345 Viral Pneumonia images.

To better process the data, we first created four classes referring to four possible results -- COVID,  Lung Opacity,  Normal, and Viral Pneumonia. Following this step, we further normalized the images by dividing 255 to each image. Also, we applied ImageDataGenerator technique to making the data augmentation. At the end, we generated train and test data set with image size 299\*299 and color in gray (So the size of each image is 299\*299\*1) . For validation split, due to the limited computation power, we now set the training set 0.1 and test set 0.9. Below is an example of the image.

女子的脸部特写

低可信度描述已自动生成

Covid-1.png

图片包含 照片, 看着, 瀑布, 猫

描述已自动生成

Lung-opacity-1.png

模糊照片里的男人

中度可信度描述已自动生成

Normal-1.png

图片包含 照片, 关, 男人, 游戏机

描述已自动生成

Viral Pneumonia-1.png

# **METHOD**

We proposed one architectures CNN to do the image classification. We totally built three CNN architectures with different layers and hyperparameters. The input of our neural network is the pixel data of  2,119 images in train dataset  belonging to 4 classes (Covid, Lung-Opacity, Normal, Viral Pneumonia). The output of our neural network is the prediction of which class the images belong to.

For the first CNN model,

For the first layer, we added a convolutional layer with 16 filters of 7 \* 7 size and the RELU activation function, with stride = 1 and padding = 2. And then we added a MaxPooling layer with a 4 \* 4 filter (stride = 2).

For the second layer, we added a convolutional layer with 32 filters of 5 \* 5 size and the RELU activation function, with stride = 1 and padding = 2. And then we added a MaxPooling layer with a 2 \* 2 filter (stride = 2) .

For the third layer, we added a convolutional layer with 64 filters of 3 \* 3 size and the RELU activation function, with stride = 1 and padding = 2. And then we added a MaxPooling layer with a 2 \* 2 filter (stride = 2)

And then, we flatten the neural data derived from the third layer and added three fully-connected layers, which have  RELU activation functions and have separately 512, 128 and 64 neurons.

Finally, we added the final fully-connected layer which has 4 neutrons and have softmax activation function.

To be noted that after each convolutional layer we have a spatial2D dropout layer with 0.2 rate, and after each dense layer, we have a dropout layer with 0.2 rate.

The below image shows parameters used in our first CNN model:

表格

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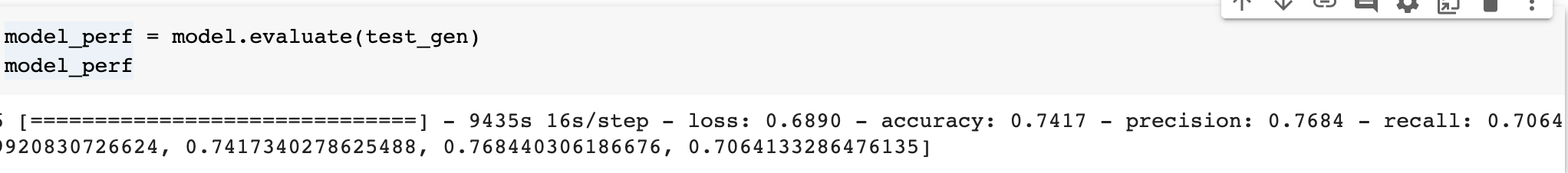
We choose cross-entropy as our loss function since we focus on a classification problem.

For the results from train dataset, after training of 50 epochs under the first CNN, the summary table of precision, recall and accuracy is shown below:

文本

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For the test dataset, the summary of precision, recall and accuracy is shown below:



For the second CNN model, it is built based on the first one. The difference between the second and the first model is that the second has doubled convolutional layers. The first CNN model has 3 convolutional layers, and we added 3 exactly same convolutional layers to the second model, so the second model have 6 convolutional layers. All the other hyperparameters are kept the same.

The below image shows parameters used in our first CNN model:

表格

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表格

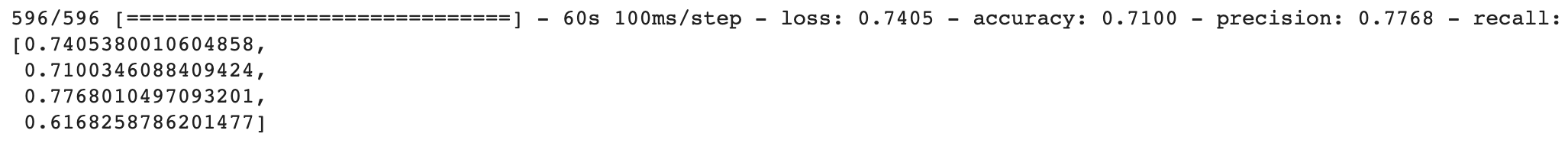
描述已自动生成

For the results from train dataset, after training of 50 epochs under the second CNN, the summary table of precision, recall and accuracy is shown below:

文本

描述已自动生成

For the test dataset, the summary of precision, recall and accuracy is shown below:



For the third CNN model, the only difference of it from the first CNN model is that we changed the drop out rate from 0.2 to 0.1 for each dropout layer. Thus, the CNN architecture of the third model is the same as the first model and we will not show the parameter summary.

For the results from train dataset, after training of 50 epochs under the third CNN, the summary table of precision, recall and accuracy is shown below:

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# **Results and discussion**

Firstly, the summary table of results for three CNN models is attached below:

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For the explanation of the results, we will use TP, TN, FP,FN to represent four kinds of prediction results: true positive(prediction is COVID while actual result is COVID), true negative(prediction is NORMAL while actual result is NORMAL), false positive(prediction is COVID while actual result is NORMAL), false negative(prediction is NORMAL while actual result is COVID), and precision, recall and accuracy could be expressed using the below formulas:

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

Accuracy = (TP+TN)/(TP+TN+FP+FN)

Using results derived from test dataset to explain, our CNN1 model correctly predicted 69.62% COVID observations among all the observations predicted as COVID; correctly predicted 55.85% COVID observations among all the actual COVID observations; and make 65.2% correct diagnosis among all the observations. Similarly, our CNN2 model correctly predicted 72.82% COVID observations among all the observations predicted as COVID; correctly predicted 61.68% COVID observations among all the actual COVID observations; and make 71% correct diagnosis among all the observations. Our CNN3 model correctly predicted 72.52% COVID observations among all the observations predicted as COVID; correctly predicted 59.25% COVID observations among all the actual COVID observations; and make 67.08% correct diagnosis among all the observations.

Secondly, we will show the change of loss, accuracy, precision and recall with 50 epochs for each CNN model, we could find the loss decreases with epochs increasing, accuracy, precision and recall increase with epochs increasing:

For CNN1,

图表, 折线图

描述已自动生成

For CNN2,

图表, 折线图

描述已自动生成

For CNN3,

图表, 折线图

描述已自动生成

Thirdly, we will show the confusion matrix for each CNN model, we could find for all the three models, they worked well when predicting the actual normal observations as normal but not when predicting the COVID observations as COVID. Thus the false negative is relatively high for all the CNN models:

For CNN1,

电脑萤幕的截图

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For CNN2,

电脑萤幕的截图

描述已自动生成

For CNN3,

电脑截图

描述已自动生成

# **Conclusion and future work**

Our CNN2 model worked best when detecting COVID using Chest X-Ray images, achieving test accuracy over 70%. Also, CNN generally works well when making image classification, and the mere modifications to CNN architecture could not apparently improve the model’s performance. However, the magnitude of train dataset plays in a key role when improving model’s accuracy but training a large dataset requires advanced computational power, which is usually limited. Thus, for the future work, we should focus on enhance the algorithm, which should not be a simple CNN, but should incorporate more pre-trained models and transfer learning techniques. Both my partner and I learned a lot from the group work. It is our first opportunity to apply the deep learning techniques in a practical context – detecting COVID using Chest X-Ray images. We realized the importance of dataset’s magnitude and algorithm’s complexity to the model’s accuracy. Also, we both found each other help us to think outside of the box since different individuals have different perspective. Plus, firstly we thought the project looking intermediating but we found the power of cooperation helped us to overcome difficulties during the project process.

Contribution distribution:

Xinran Cui: search for dataset, wrote the proposal

Li Ju: preprocessed data, set up CNN architecture

Cooperated part (everyone done half work):

Train three CNN models, literature review, process report and final report writing, video recording

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