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Deep CNN Model for COVID-19 Infection Detection

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Abstract: This paper focuses on the use of deep learning model in diagnosing Coronavirus disease (COVID-19) lung infection. For this purpose, this work employed pretrained AlexNet model for two-class classification problem (i.e., "COVID" and "NONCOVID"). It is also the objective of this work to provide quantitative assessment of the classifier's reliability based on the performance metrics. We used 80 chest X-ray images (i.e., 40 images of COVID-19 infected patients and 40 of healthy individuals) in this preliminary study. This work evaluates the performance of the trained classifier and observed relatively good performance in the prediction of validation data using outcomes from three best training runs. The mean accuracy, specificity, sensitivity, precision, error rate and false positive error are given by 87.5%, 83.3%, 91.67%, 85%, 12.5% and 16.67% respectively. It is concluded that the trained model is able to perform relatively well in classifying COVID-19 X ray images. In future, more data could be used in the training to increase accuracy of the model. Further possible attempt also includes the use of chest images from other imaging technologies in the training to give higher variability on the choice of dataset using which a deep learning model can train on.

Keywords: COVID-19, X-ray, AlexNet

1. Introduction

Coronaviruses (CoVs) belong to the sub-group of Orthocoronavirinae inside the family of Coronaviridae. There are four genera within the Orthocoronavirinae subfamily, namely Alpha (α-CoV), Beta (β-CoV), Gamma (γ-CoV) and Delta (δ-CoV)[1, 2]. The CoV genome is an enveloped, positive-single-stranded Ribonucleic Acid (RNA) with a size ranging between 26 and 32 kbs in length [2]. Both α- and β-CoV are well known to contaminate mammals, whilst δ-CoV and γ-CoVs infect birds. Over the span of two decades, the outbreaks of three deadly β-CoVs are reported. They are severe acute respiratory syndrome (SARS-CoV and SARS-CoV-2, which is the cause of COVID-19) and Middle East respiratory syndrome (MERS) [2].

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Current research suggests that effective transmission of COVID-19 from infected individuals of both symptomatic and asymptomatic to uninfected contacts can be from respiratory droplets, aerosols, and direct contact [3]. The main and infamous symptoms of COVID-19 infections including fatigue, fever and pneumonia that could advance into acute respiratory distress (ARDS) in patients [4]. The diagnosis can be based on imaging apparatus such as chest X-ray and computerized tomography (CT). Some of these patients may develop fatal complications including organ failure, septic shock, pulmonary edema and severe pneumonia [5, 6] as the disease progresses from mild to critical condition. Notably, patients who required intensive care support were older and had multiple comorbidities including cardiovascular, cerebrovascular, endocrine, digestive, and respiratory disease. Those in intensive care were also more likely to suffer from dyspnoea, dizziness, abdominal pain, and anorexia [5].

To date, COVID-19 has spread rapidly around the world, with more than 6 million confirmed cases and over 400 thousand deaths as of June 2020.As the global threat of COVID-19 continues to increase, World Health Organization (WHO) has declared this outbreak a public health emergency of international concern (PHEIC) [7]. This pandemic has placed enormous burden on healthcare and resources in diagnosis and treatment of the disease.

Previous study by [8] developed an open source datasets and proposed a Convolutional Neural Network (CNN) framework to differentiate COVID-19 cases from other pneumonia cases. The authors presented a 3-step technique to fine-tune a pre-trained ResNet-50 architecture to improve the model's performance to reduce training time. Another study by [9] proposed a fully automated deep learning system for COVID-19 diagnosis and prognosis using a CT scan. The authors used 4106 CT images to train and validate the performance of the pretrained DenseNet121 network for lung segmentation in chest CT images. Other related studies included [10] that compared multiple CNN models for classification of CT images into COVID-19, Influenza viral pneumonia, and no-infection. The corresponding study used ResNet-18 and ResNet-23 network for classification of CT images. Meanwhile, [11] used ResNet50 and VGG16 network to diagnose COVID-19 infection using 204 chest X-ray images (102 COVID-19 cases and 102 pneumonia cases). Most of these models, however, require significant amounts of computing time and memory resource. Continue research on the efficient and time saving diagnosis of SARS-CoV-2 is therefore needed to reduce the burden of healthcare services. This work is motivated by the aforementioned challenges, we herein present the use of pretrained AlexNet for rapid classification of COVID-19 infection using chest X-ray images.

2. Methods

This study used 80 chests X-ray images publicly available from Kaggle website (https://www.kaggle.com/praveengovi/coronahack-chest-xraydataset) for demonstration purposes. All works are carried out using MATLAB R2020b software. The methodology workflow is in Figure 1.

Figure 1: General workflow of tasks involved in this project

2.1 Load pretrained network and data preparation

In MATLAB, a *fullfile* function was used to provide the full path to the folder where the images were saved. This function allows loading of the chest X-ray images via *imageDatastore* function. These images were labeled according to the folder names where they reside: COVID and NONCOVID. Once called into MATLAB platform, they are stored as object property data in MATLAB. A data store allows storing of large dataset, even if the data do not fit into the memory, and enables efficient reading of image batches during CNN training. Next, the chest X-ray images of each class are divided into training and validation data sets. This works used 80 % of the images randomly chosen for training and 20% for validation. For this, *splitEachLabel* function is used to split the images datastore. Next, the pretrained AlexNet was called into MATLAB by using *alexnet* function. This required installation of a Deep Learning Toolbox™ prior to its accessibility. This study used *analyzeNetwork* function to display the AlexNet network architecture and extract information of each layer. After that, *inputSize* function is used to resize the input images size to 277×277×3 pixels.

2.2 Modification of pretrained network

The *lgraph* function is used extract the layer graph from the pretrained AlexNet network for training on the investigated images. This is for the purpose of modifying the network for the specific task of X-ray COVID-19 diagnosis. The extracted layers were replaced with a new layer (*FullyConnectedLayer and Convolution2DLayer*) which is adapted to the new dataset. The last two layers were replaced in this work, and they were found using *findLayersToReplace* function.

2.3 Image preprocessing and network training

The pretrained network AlexNet requires the input images of size 277×277×3, so *gray2rgb* function is used to embed gray images into three planes of red, green, blue (RGB) images. Following this, augmentation operations are used to increase the variability and numbers of images used in training process. This work used three methods for augmentation, which strategy is well-known to prevent overfitting. This includes flipping of the training images along the vertical axis, the scale ranged from 0.9 to 1.1 for horizontal and vertical directions, these images were also randomly translated up to 30 pixels horizontally and vertically. Each image has been randomly augmented using the schemes described earlier, these images replacing the original images were used in the training giving 64 images used in the training. During the training it is important to specify hyperparameters value, and the performance of the model is highly dependent on the chosen values. In this work, properties such as transferred layer weights are set as 0.0003, number of epochs has been set as 6, batch size number was chosen as 10 and learn rate was 10. The MATLAB software would validate the AlexNet network every *ValidationFrequency* iterations (chosen as 35) as training progressed. The modified network was trained for 10 times. The results from the best three runs (from training accuracy) were further used for model performance evaluation and analysis

2.4 Network performance evaluation

After the classification, the performance of trained AlexNet were assessed using validation results obtained from three best trained models. The *confusionmat* function is used to produce and display the confusion matrix. This table is useful to determine the performance metrics values of the trained network. In this study, different performance metrics are considered for evaluating the model's prediction capability, they are namely accuracy, specificity, sensitivity, precision, error rate, and the false positive error rate. Sensitivity or true positive rate (TPR) is often referred to as recall (REC) [12], whereas specificity is the true negative rate (TNR). For the error rate and false positive rate, the best value is 0 %, while the worst is 100 %. Meanwhile the best value for accuracy is 100%, while the worst is 0%. This is the same for sensitivity, specificity and precision. Finally, the worst false positive rate is 100%, and the best is 0% [13]. The formulas of the considered performance measures are shown in Table 1.

Table 1: The considered performance metrics

Performance measure	Formula
Accuracy, *ACC*	$ACC = \frac{TP + TN}{TP + TN + FN + FP} = \frac{TP + TN}{P + N}$
Sensitivity, *SN*	$SN = \frac{TP}{TP + FN} = \frac{TP}{P}$
Specificity, *SP*	$SP = \frac{TN}{TN + FP} = \frac{TN}{N}$
Precision, *PREC*	$PREC = \frac{TP}{TP + FP}$
Error Rate, *ERR*	$ERR = \frac{FP + FN}{TP + TN + FN + FP} = \frac{FP + FN}{P + N}$
False Positive Rate, *FPR*	$FPR = \frac{FP}{TN + FP} = 1 - SP$

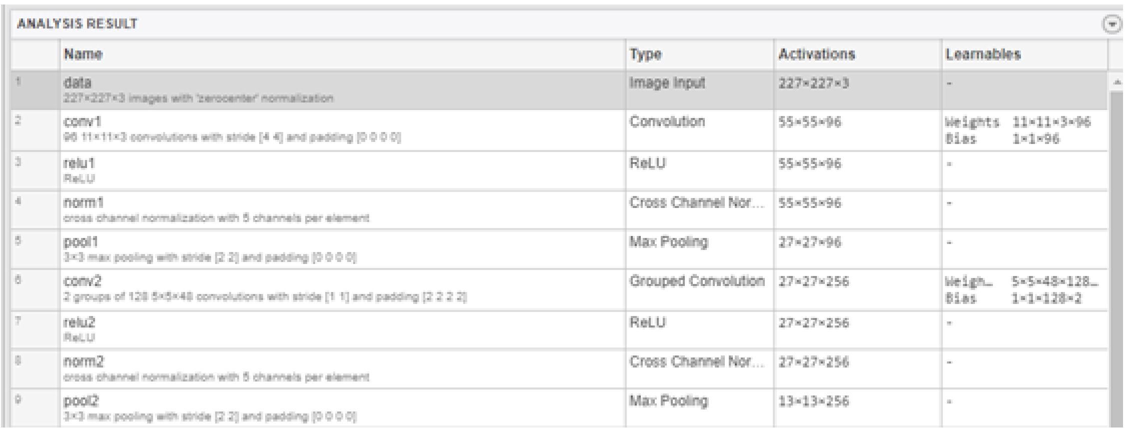
TN = true negative
TP = true positive
FP = false positive
FN = false negative
P = total positive = TP+FP
N = total negative = TN+FN

2.5 Display result

At the end of the process, the predicted class (i.e. label with highest probability) and true class (i.e. label) of chest X-ray images chosen from validation dataset would be displayed for interpretation of its users.

3. Results and Discussion

In the simulation, AlexNet was trained to diagnose COVID-19 using chest X-ray images. Figure 2 shows a diagram of pretrained AlexNet layer architecture interactively visualized using *analyzeNetwork* from Deep Learning toolbox. The architecture shows the different layers and arrangement of convolutional, pooling and rectified linear activation (ReLU) layer in extraction of important features required for classification.



ANALYSIS RESULT

	Name	Type	Activations	Learnables
1	data 227×227×3 images with 'zerocenter' normalization	Image Input	227×227×3	-
2	conv1 96 11×11×3 convolutions with stride [4 4] and padding [0 0 0 0]	Convolution	55×55×96	Weights 11×11×3×96 Bias 1×1×96
3	relu1 ReLU	ReLU	55×55×96	-
4	norm1 cross channel normalization with 5 channels per element	Cross Channel Nor...	55×55×96	-
5	pool1 3×3 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	27×27×96	-
6	conv2 2 groups of 128 5×5×48 convolutions with stride [1 1] and padding [2 2 2 2]	Grouped Convolution	27×27×256	Weigh... 5×5×48×128... Bias 1×1×128×2
7	relu2 ReLU	ReLU	27×27×256	-
8	norm2 cross channel normalization with 5 channels per element	Cross Channel Nor...	27×27×256	-
9	pool2 3×3 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	13×13×256	-

Figure 2: Pretrained AlexNet layers

Figure 3 shows the performance of the AlexNet network in image classification as the training process was in progress. Also shown in the figure is the accuracy of the trained model using validation data and the time taken for the training using LENOVO Ideapad 110 with AMD A8 and 4GB RAM. This work runs the simulation for 10 times. On average, the time taken to train a AlexNet network is 656.67 seconds or approximately 10 minutes and 59 seconds. The lower diagram of Figure 3 shows loss against iteration indicating reduction in loss with training process. Table 2 shows the training and validation accuracy in 10 separate training sessions.

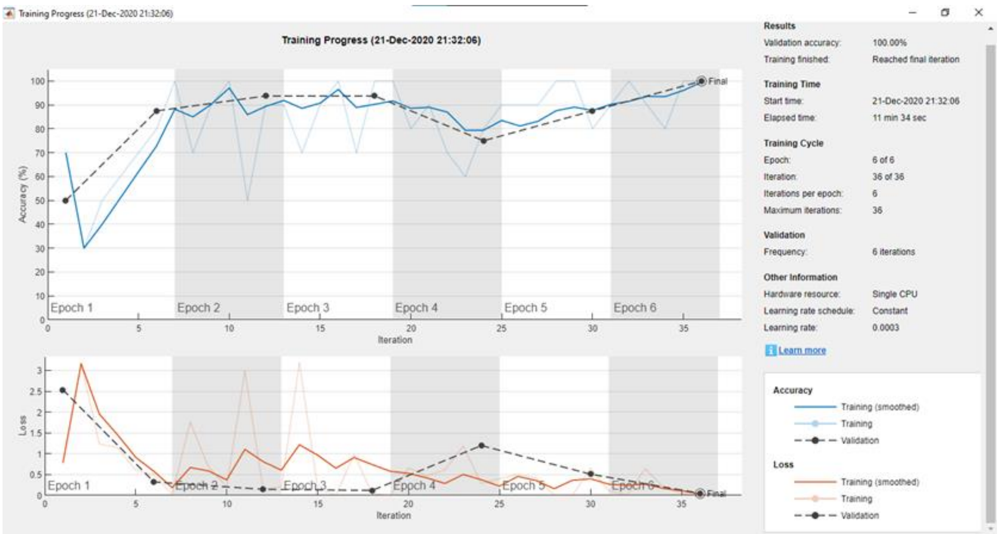


Figure 3: Plot of training progress for chest X-ray images classification

Table 2: Training and validation accuracy for 10 separate training sessions

Training session index, *i*	Training accuracy, ACC (in %)	Validation accuracy, ACC (in %)
1	100	100
2	90	68.75
3	81.25	81.25
4	100	81.25
5	100	100
6	80	87.50
7	90	68.75
8	100	87.50
9	100	75
10	80	93.75

According to Table 2, results from $i = 1$ are among the best (in terms of both training and testing accuracy) identified from the training sessions. This is followed by $i = 8$ and 9. These are the best three trained models chosen for further analysis in Table 3. The confusion matrix of validation images using the trained model from $i = 1$ is shown in Figure 4.

Table 3: Calculated performance metrics based on the confusion matrix for the chosen training sessions.

Performance metric	Training session		
	***i*=1**	***i*=8**	***i*=9**
Error Rate	0%	12.5%	25%
Accuracy	100%	87.5%	75%
Sensitivity	100%	100%	75%
False Positive Rate	0%	25%	25%
Specificity	100%	75%	75%
Precision	100%	80%	75%
Training accuracy	100%	100%	100%
Validation accuracy	100%	87.50%	75%

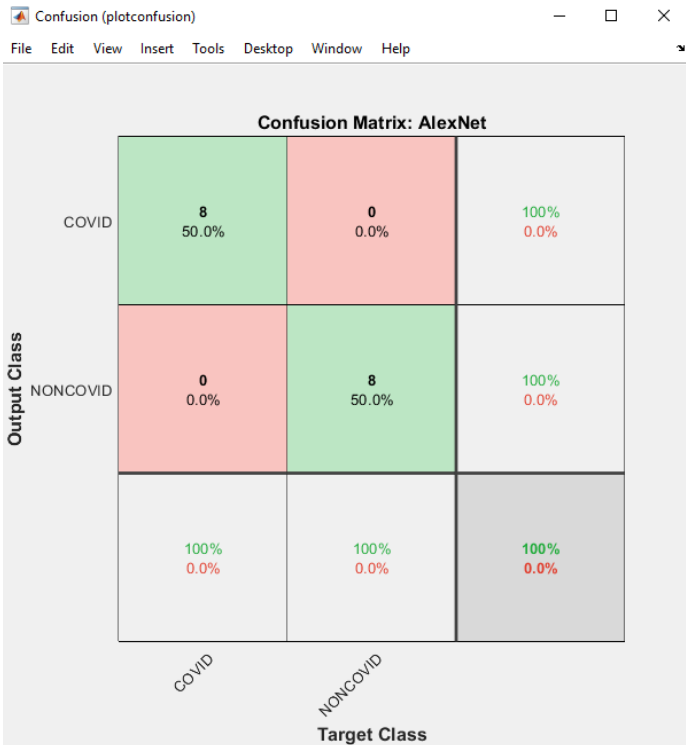


Figure 4: Confusion matrix on validation dataset from training session *i* = 1.

Figure 5 shows the classified results of chest X-rays images for one of the trained sessions (*i*=*9*) since it produced inferior results as compared to the rest in Table 3. The diagram, also shows the probability of classification outcome, i.e., whether patient is infected or not infected by COVID-19.

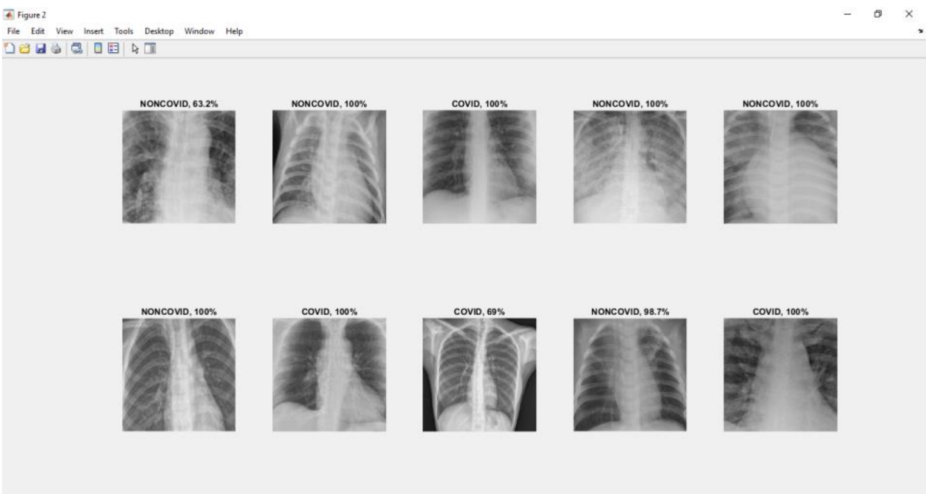


Figure 5: Example of probability score of classification outcome on chest X-ray images.

4. Conclusion

This work demonstrated the feasibility of using a modified pretrained AlexNet to diagnose COVID-19 using chest X-ray dataset. This work found relatively good accuracy, specificity, sensitivity and precision of near 100% in most of the validation sessions, while low error rate and false positive error were also observed. This work hypothesized future improvement can be made to further improve classification accuracy of the model. This includes the use a Residual Neural Network (ResNet) for classification as this model was previously reported in [8] to yield a lower error rate than AlexNet [8].

In addition, adaptive cross checking such as, class activation mapping (CAM), could also be used for this purpose. Using CAM, one can check if the network was "confused" by a particular part of an input image, which could result in incorrect prediction. The ability to identify the false predictions where the model is built on would allow one to produce a network with better classification performance [14]. This is in addition to the inclusion of more data in the training. This may include the use of CT images in the future to increase variability in the images and the size of dataset.

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References

[1] D. Yang and J. L. Leibowitz, “The structure and functions of coronavirus genomic 3’ and 5’ ends,” Virus Res., vol. 206, pp. 120–133, 2015.

[2] S. A. Ali, M. Baloch, N. Ahmed, A. A. Ali, and A. Iqbal, “Journal of Infection and Public Health The outbreak of Coronavirus Disease 2019 (COVID-19)— An emerging global health threat,” J. Infect. Public Health, vol. 13, no. 4, pp. 644–646, 2020.

[3] A. Patel, D. B. Jernigan, and 2019-nCoV C D C Response Team, “Initial Public Health Response and Interim Clinical Guidance for the 2019 Novel Coronavirus Outbreak.,” Morb. Mortal. Wkly. Rep., vol. 69, no. 5, 2020.

[4] S. Cov, G. Ward, and L. C. Hospital, “Letter to the editor,” vol. 50, pp. 293–296, 2020.

[5] C. Sohrabi et al., “World Health Organization declares global emergency : A review of the 2019 novel coronavirus (COVID-19),” Int. J. Surg., vol. 76, no. February, pp. 71–76, 2020.

[6] B. M. Kaess, M. G. Larson, N. M. Hamburg, J. A. Vita, D. Levy, and E. J. Benjamin, “and Incident Hypertension,” vol. 308, no. 9, pp. 875–881, 2012.

[7] L. M. Lim, S. Li, A. Biswas, and M. Choolani, “Special Report and pregnancy,” Am. J. Obstet. Gynecol., vol. 2019, 2020.

[8] M. Farooq and A. Hafeez, “COVID-ResNet: A Deep Learning Framework for Screening of COVID19 from Radiographs,” 2020.

[9] S. Wang et al., “A Fully Automatic Deep Learning System for COVID-19 Diagnostic and Prognostic Analysis,” Eur. Respir. J., p. 2000775, 2020.

[10] Charmain Butt, “covid19: Deep Learning System to Screen Coronavirus Disease 2019 Pneumonia,” 2020.

[11] L. O. Hall, R. Paul, D. B. Goldgof, and G. M. Goldgof, “Finding Covid-19 from Chest X-rays using Deep Learning on a Small Dataset,” pp. 1–8, 2020.

[12] H. G. Lewis and M. Brown, “A generalized confusion matrix for assessing area estimates from remotely sensed data,” Int. J. Remote Sens., vol. 22, no. 16, pp. 3223–3235, 2001.

[13] A. K. Santra and C. J. Christy, “Genetic Algorithm and Confusion Matrix for Document Clustering,” Int. J. Comput. Sci. Issues, vol. 9, no. 1, pp. 322–328, 2012.

[14] T. Zebin and S. Rezvy, “COVID-19 detection and disease progression visualization: Deep learning on chest X-rays for classification and coarse localization,” Appl. Intell., 2020.