Coronavirus Disease (COVID-19) Pneumonia and Influenza Virus Pneumonia Detection Using Convolutional Neural Network

MSDS 498 - SL SEC60
Northwestern University

Julianna Antonchuk
julianna.antonchuk2021@u.northwestern.edu

Philip Melanchthon
solomonmelanchthon2021@u.northwestern.edu

Benjamin Prescott
benjaminprescott2022@u.northwestern.edu

Robin Singh
robinsingh2022@u.northwestern.edu

24 October, 2021

Abstract

In the research project, we develop a convolutional neural network (CNN) optimized to analyze and differentiate among visual imagery of human lungs impacted by coronavirus disease (COVID-19) pneumonia and influenza virus pneumonia. The recent study on the comparison of the computed tomography (CT) manifestations of COVID-19 Pneumonia and Influenza Virus Pneumonia conducted by Lin (2021) concluded that the most lesions in patients with COVID-19 pneumonia were located in the peripheral zone and close to the pleura, whereas influenza virus pneumonia was more prone to show mucoid impaction and pleural effusion. However, differentiating between COVID-19 pneumonia and influenza virus pneumonia in clinical practice remains difficult. Therefore, by employing computer vision methods, we aspire to devise an algorithmic solution that, in a complementary way, supports diagnostic radiology in differentiating, timely and accurately, between COVID-19 and non-COVID-19 pneumonia. Since the chest CT appearance of COVID-19 pneumonia is thought to be nonspecific, it presents a challenge to identify an optimal architecture of a convolutional neural network that classifies with a high sensitivity among the pulmonary inflammation features of COVID-19 and non-COVID-19 pneumonia. Rahman (2021) states that COVID-19 radiography images observe unavailability and quality issues impacting the diagnosis

process and affecting the accuracy of the deep learning detection models. A significant scarcity of COVID-19 radiography images introduces an imbalance in data motivating to use over-sampling techniques. In the study, we include an extensive set of X-ray imaging of human lungs with COVID-19 pneumonia, influenza virus pneumonia, and healthy biomarkers to achieve an extensible and accurate CNN model.

Keywords: *artificial neural network, computer vision, convolutional neural network, CNN, ConvNet, artificial intelligence software, coronavirus disease, coronavirus disease pneumonia, influenza virus pneumonia, pulmonary inflammation, chest computed tomography, chest X-ray, diagnostic radiology, radiography images, Azure machine learning service, Azure.*

Background

In December 2019, an epidemic caused by severe acute respiratory syndrome corona-virus 2 (SARS-CoV-2) broke out in Wuhan, China. Coronavirus disease, i.e. COVID-19, results from SARS-CoV-2 infection, has caused human-to-human transmission and death worldwide.

As of October 2021, global statistics, reported to the World Health Organization, demonstrate more than 242 million confirmed cases of COVID-19, including almost 5 million deaths. The new coronavirus causes severe inflammation in human lungs, damaging the cells and tissue that line the air sacs. The main pathologic manifestation of COVID-19 is pulmonary inflammation: CT manifestations vary and include ground-glass opacity (GGO), consolidation, or GGO mixed with consolidation.

Influenza is a highly contagious disease that occurs worldwide. Influenza viruses (mostly type A, occasionally type B) cause influenza virus pneumonia, resulting in seasonal epidemics of community-acquired pneumonia. The main CT manifestations of influenza virus pneumonia are GGO and consolidation with air bronchogram, interlobular septal thickening, centrilobular nodules, and reticular opacities ("CT Manifestations of Coronavirus Disease (COVID-19) Pneumonia and Influenza Virus Pneumonia: A Comparative Study", 2021).

Radiologists in China and in the United States distinguished coronavirus disease 2019 from viral pneumonia at chest CT with moderate to high accuracy. Compared with non-COVID-19 pneumonia, COVID-19 pneumonia was more likely to have a peripheral distribution (80% vs 57%, $P < 0.001$), ground-glass opacity (91% vs 68%, $P < 0.001$), fine reticular opacity (56% vs 22%, $P < 0.001$), and vascular thickening (59% vs 22%, $P < 0.001$), but it was less likely to have a central and peripheral distribution (14% vs 35%, $P < 0.001$), pleural effusion (4% vs 39%, $P < 0.001$), or lymphadenopathy (3% vs 10%, $P = 0.002$) ("Performance of Radiologists in Differentiating COVID-19 from Non-COVID-19 Viral Pneumonia at Chest CT", 2020).

The recent study on the comparison of the CT manifestations of COVID-19 pneumonia and influenza virus pneumonia conducted by Lin (2021) demonstrated that the most lesions in patients with COVID-19 pneumonia were located in the peripheral zone and close to the pleura, whereas influenza virus pneumonia was more prone to show mucoid impaction and pleural effusion. The studies conducted by Lin (2021) and Bai (2020) are aligned in their findings. However, differentiating between COVID-19 pneumonia and influenza virus pneumonia in clinical practice still remains difficult.

Therefore, we have developed an artificial neural network - an algorith-

mic approach to complement a radiological diagnosis. In our experimentation, we consider convolutional neural network topologies and architectures to determine a highly performant model classifying among healthy lung biomarkers, COVID-19 and non-COVID-19 pneumonia images.

In the earlier project leading to the current capstone project, the classification was performed only on two classes of X-ray images: healthy human lungs and those impacted by COVID-19 pneumonia. We use the model as an indirect baseline while constructing architectures for a multi-class image classification.

In the research, we employ an extensive set of publicly available X-ray imaging of human lungs with COVID-19 pneumonia, influenza virus pneumonia, and healthy biomarkers.

We perform model experimentation on the Azure machine learning platform which has a wide range of productive experiences to build, train, and deploy machine learning models as well as foster team collaboration. Leveraging the auto-scaling compute feature of the Azure machine learning platform allows us to manage compute resources for better training distribution, rapid testing, and validation, as well as model deployment. A part of the experiment design, we would like to compare the model processing time using available compute resources, i.e. evaluate model training time on CPU and GPU clusters.

Data Collection

In the research, we employ publicly available X-ray imaging of human lungs with COVID-19 pneumonia, influenza virus pneumonia, and healthy biomarkers. Data was collected from Kaggle datasets and Mendeley Data, a secure cloud-based repository. The input data are represented by three classes:

1. X-ray images of human lungs with COVID-19 pneumonia (4, 152),
2. X-ray images of human lungs with influenza virus pneumonia (4, 494), and
3. X-ray images of healthy human lungs (10, 860).

Research Design

In order to achieve a highly accurate and performant model, we set up experimentation where we iteratively find a better model. Thus, we perform hyperparameter tuning, comparing network performance when changing learning rate, number of epochs, batch size, activation function, number of hidden layers, dropout regularization, etc. We tune only one hyperparameter at a time, holding others constant. We are interested in applying grid search and random search to determine hyperparameter candidates. As a part of experimentation, we might

consider applying data augmentation, a data-space solution to the problem of limited data. The image augmentation techniques include geometric transformations, color space augmentations, kernel filters, mixing images, random erasing, feature space augmentation, adversarial training, generative adversarial networks, neural style transfer, and meta-learning. Attempting a more deep network topology is an essential step in the research experimentation along with hyperparameter tuning: here we would like to iteratively compare deeper and more shallow networks, evaluate padding (same, valid) and pooling (average, max) techniques. Working with the auto-scaling compute feature of the Azure machine learning platform, we are interested in evaluating end-to-end model processing time on CPU and GPU clusters.

In the initial experimentation phase, we identified a convolutional neural network with 512 units, followed by a pooling operation for two-dimensional spatial data with a size of $2x2$, and a flattened layer of 64 nodes resulting in 95% accuracy. We use the model as an indirect baseline while constructing architectures for multi-class image classification.

In the current phase of the experimentation, we cleaned and labeled the data. X-ray images of human lungs with COVID-19 pneumonia are labeled with 0, influenza virus pneumonia is identified with 2, and images with healthy

biomarkers are marked with 1. The first iteration of the model leveraged a single convolutional layer consisting of 512 filters, followed by a single pooling layer (see Appendix, fig.1). This model was trained on a compute instance with 24 cores, 224 GB RAM, and 4 GPUs, resulting in a training duration of 14 minutes per epoch. We leveraged early stopping as a regularization technique, and to help minimize the overall training time, resulting in our first model reaching peak performance at epoch 7. The single convolutional layer model demonstrated a loss of 0.0496, an accuracy of 0.9855, a validation loss of 0.4302, and a validation accuracy of 0.91 (see Appendix, fig.2).

As the next steps, we would like to follow the aforementioned experimentation plan to achieve the best performing model using the performance benchmarking across their processing time, loss, accuracy, and a number of parameters.

Literature Review

In our research, we investigate recently conducted medical research and studies on the differences in computed tomography manifestations of coronavirus disease (COVID-19) pneumonia and those of influenza virus pneumonia. Primarily, we leverage the findings from the research "Performance of Radiologists

in Differentiating COVID-19 from Non-COVID-19 Viral Pneumonia at Chest CT" (Bai et al., 2020) and from the comparative study "CT Manifestations of Coronavirus Disease (COVID-19) Pneumonia and Influenza Virus Pneumonia: A Comparative Study" (Lin et al., 2021). The discoveries provide points of reference for distinguishing SARS-CoV-2 infection from influenza virus infection based on the CT morphologic features and quantitative parameters of COVID-19 pneumonia and influenza virus pneumonia. However, it is stated that differentiating between COVID-19 pneumonia and influenza virus pneumonia in clinical practice still presents a challenge. Our study leverages two-dimensional radiography images, we refer to the findings detected via computer tomography as a reference and build a knowledge base around the studied conditions.

In our study, we reference the paper "Deep Learning–Driven Automated Detection of COVID-19 from Radiography Images: a Comparative Analysis" (Rahman et al., 2021) since it covers challenges due to the unavailability and quality issues related to COVID-19 radiography images impacting the diagnosis process and affecting the accuracy of the detection model. The challenge of the unavailability speaks to having a sufficient number of X-ray images of pneumonia-affected and normal lungs and a significant scarcity of COVID-19 radiography images introducing an imbalance in data. The researchers invoked techniques of

Synthetic Minority Over Sampling (SMOTE), borderline SMOTE, and safe level SMOTE. Among deep learning–based diagnosis approaches, the researchers discuss transfer learning, ensemble learning, domain adaptation, cascaded networks along with some other approaches.

The authors are concerned about the limitations of the existing deep convolutional neural networks like ResNet, DenseNet, and VGGNet due to having a deep structure with excessively large parameter sets and lengthy training time. Whereas in Transfer Learning (TL), knowledge acquired from the training on one dataset is reused in another task with a related dataset, yielding improved performance and faster convergence.

Chest X-ray image of a COVID-19 patient has a different distribution but similar characteristics as that of pneumonia, allowing a promising usage of the domain adaptation technique, i.e. using feature adversarial adaptation.

The paper speaks to the significant contributions of ensemble learning towards achieving an accurate result for COVID-19 detection as well. For instance, Goodwin combined 12 models (Resnet-18,50,101,152, WideResnet-50,101, ResNeXt-50,101, MobileNet-v1, Densenet-121,169,201) demonstrating better results (Goodwin et al., 2020). Similarly in the study "Pneumonia detection in chest X-ray images using an ensemble of deep learning models" (Kundu et al.,

2021), the researchers employed deep transfer learning to handle the scarcity of available data and designed an ensemble of three convolutional neural network models: GoogLeNet, ResNet-18, and DenseNet-121. A weighted average ensemble technique was adopted, wherein the weights assigned to the base learners were determined using a novel approach.

The results, discovered in the study "Deep Learning–Driven Automated Detection of COVID-19 from Radiography Images: a Comparative Analysis" (Rahman et al., 2021), show that the DenseNet201 model with Quadratic SVM classifier performs the best (accuracy: 98.16%, sensitivity: 98.93%, specificity: 98.77%) and maintains high accuracy in other similar architectures as well.

The recent findings on the similar detection classification problem are promising, inspiring, and useful to our experimentation.

References

[1] Bai, H., Hsieh, B., Xiong, Z. (2020). Performance of Radiologists in Differentiating COVID-19 from Non-COVID-19 Viral Pneumonia at Chest CT. Radiology. Original Research. Thoracic Imaging. Vol. 296, No. 2. https://pubs.rsna.org/doi/10.1148/radiol.2020200823

[2] Garcia-Gasulla, D., Par´es, F., Vilalta, A. (2018). On the Behavior of Convolutional Nets for Feature Extraction. Journal of Artificial Intelligence Research 61 (2018) 563-592.

[3] Ghafuri, J., Du, H., Jassim, S. (2020). Topological aspects of CNN convolution layers for medical image analysis. Proceedings Volume 11399, Mobile Multimedia/Image Processing, Security, and Applications 2020; 113990X (2020) https://doi.org/10.1117/12.2567476

[4] Goodwin, B., Jaskolski, C., Zhong, C. (2020). Intra-model Variability in COVID-19 Classification Using Chest X-ray Images. Cornell University. Electrical Engineering and Systems Science. Image and Video Processing. https://arxiv.org/abs/2005.02167

[5] Jiang, X., Wang, Y., Liu, W. (2019). CapsNet, CNN, FCN: Comparative

Performance Evaluation for Image Classification. International Journal of Machine Learning and Computing, Vol. 9, No. 6.

[6] Kundu, R., Das, R., Geem, Z. (2021). Pneumonia detection in chest X-ray images using an ensemble of deep learning models. https://doi.org/10.1371/journal.pone.0256630

[7] Lin, L., Fu, G., Chen, S. (2021). CT Manifestations of Coronavirus Disease (COVID-19) Pneumonia and Influenza Virus Pneumonia: A Comparative Study. American Journal of Roentgenology. 2021;216: 71-79. 10.2214/AJR.20.23304. https://www.ajronline.org/doi/full/10.2214/AJR.20.23304

[8] Liu, Y. (2018). Feature Extraction and Image Recognition with Convolutional Neural Networks. First International Conference on Advanced Algorithms and Control Engineering. J. Phys.: Conf. Ser. 1087 062032. https://iopscience.iop.org/article/10.1088/1742-6596/1087/6/062032

[9] Love, E., Filippenko, B., Maroulas, V. (2020). Topological Convolutional Neural Networks. Topological Data Analysis and Beyond Workshop at the 34th Conference on Neural Information Processing. Systems (NeurIPS 2020), Vancouver, Canada. https://openreview.net/pdf?id=hntbh8Zo1V

[10] Rahman, S., Sarker, S., Miraj, A. (2021). Deep Learning–Driven Automated Detection of COVID-19 from Radiography Images: a Comparative Analysis. Cognit Comput. 2021 Mar 2 : 1–30. doi: 10.1007/s12559-020-09779-5. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7921610/

[11] Rahman, T. COVID-19 Radiography Database. https://www.kaggle.com/tawsifurrahman/covid19-radiography-database

[12] Shorten, C., Khoshgoftaar, T. (2019). A survey on Image Data Augmentation for Deep Learning. Journal of Big Data volume 6, Article number: 60. https://journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0197-0

[13] Siddhartha, M. COVID CXR Image Dataset (Research). https://www.kaggle.com/sid321axn/covid-cxr-image-dataset-research

Appendix

1. Single Convolutional Layer Model: version 1.0

1.1. Architecture

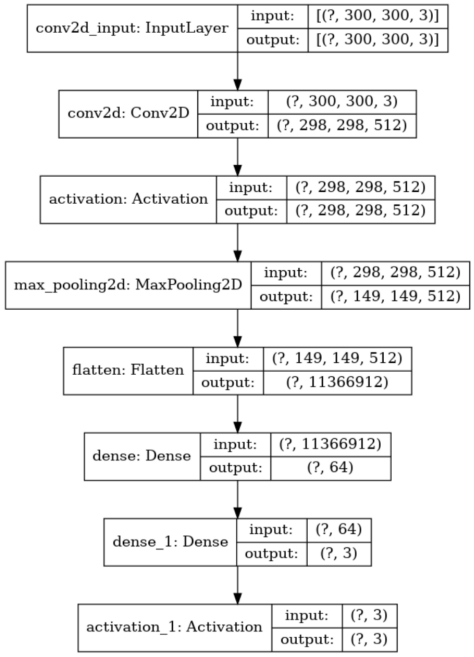

Figure 1. Single Convolutional Layer Model Architecture.

1.2. Loss and Accuracy Metrics

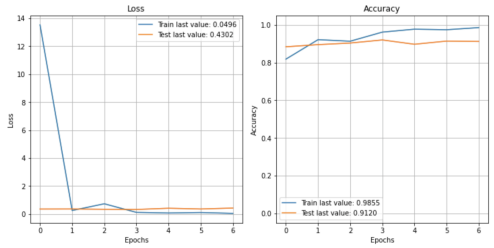

Figure 2. Loss and Accuracy Metrics.

1.3. **Confusion Matrix**

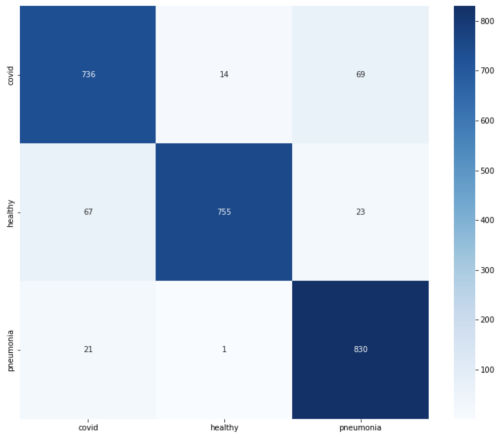

Figure 3. Confusion Matrix.