Effect of the Laplace Operator on the Performance of CoronaNet for COVID-19 Detection

April 16, 2020

Rohan Bhansali rohanmbhansali@gmail.com

Rahul Kumar rakumar2003@gmail.com

1. About the authors

Rohan Bhansali is a junior in high school that is conducting deep learning research at the Academy of Science in Loudoun County, Virginia. He is passionate about working with deep learning algorithms to solve biomedical problems to help benefit the less fortunate citizens of the world.

Rahul Kumar is a junior in high school working on machine learning research at the Academy of Science in Loudoun County, Virginia. He is ardent about using technology to help solve problems in innovative and efficient ways to help people around the world.

2. Abstract

Coronavirus disease (COVID-19) is the cause of a global pandemic that is affecting millions of people around the world. Inadequate testing resources have resulted in several people going undiagnosed and consequently untreated. However, using computerized tomography (CT) scans for diagnosis is an alternative to bypass this limitation. In this paper, we describe CoronaNet, a deep convolutional neural network that can recognize if a patient has COVID-19 from images of CT scans with 90% accuracy. We hope this algorithm can be incorporated into hospitals around the world to assist in coronavirus mitigation efforts. Additionally, we demonstrate the effectiveness of the Laplace Operator in enhancing the performance of CoronaNet. Our source code is available here.

3. Introduction

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has been identified as the virus causing coronavirus disease (COVID-19). Believed to originate in a meat market in Wuhan, China, in December 2019, COVID-19 is the name of the disease that is caused by the viral agent known as SARS-CoV-2. It is thought to have originated in the city of Wuhan, China. The disease has caused the World Health Organization to declare a global public health emergency and officially classify the disease as the cause of a pandemic. Similar to previous coronaviruses, SARS-CoV-2 is originally found in bats, and is generally consistent across different regions. COVID-19 can cause mild to severe illness that if becomes more severe, can cause pneumonia, organ failure, and death. Symptoms of the disease include fever, dry cough, shortness of breath, and fatigue. The disease spreads through respiratory particles which are produced when an infected person either sneezes or coughs. These particles must be taken into the body through the nose, mouth, or eyes. COVID-19 has spread globally to affect at least 2 million people in 184 countries at the time of publication. The worldwide extent of COVID-19 has resulted in over 130,000 deaths. Those at risk belong primarily to older demographics with historically compromised immune systems or pre-existing medical conditions such as asthma, diabetes, and heart disease, as well as those with compromised lungs.

Although many countries began preparations for the spread of the disease relatively early, the effects of the pandemic are still widespread and proliferating. In many parts of the world, a massive shortage of Reverse Transcription Polymerase Chain Reaction (RT-PCR) tests is contributing to an inability to properly combat the pandemic. One way in which this problem could be alleviated is through the use of computed tomography (CT) scans for diagnosis. In CT scans, COVID-19 manifests itself as ground-glass opacities (GGOs) and consolidation with or without vascular enlargement, interlobular septal thickening, and air bronchogram sign. CT scans are much faster and more accessible than RT-PCR tests, allowing for easier and more quickly acting diagnostics.

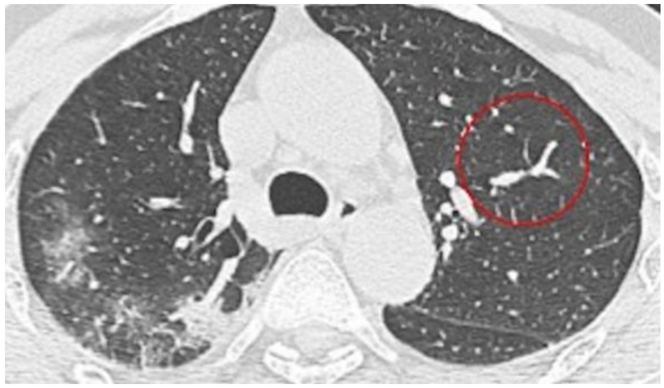
More importantly, using CT scans has been shown to be an effective and accurate method for diagnosing COVID-19. RT-PCR tests have been shown to . Thus, the purpose of this paper is to apply convolutional neural networks to distinguish images with COVID-19 using CT scans.

4. Method

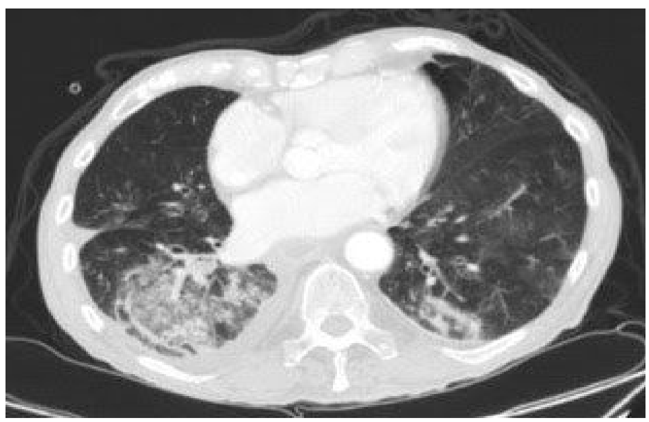
1. *Dataset*

The dataset that was used in this study was produced by researchers at the University of California at San Diego (He, Xie, Zhao, Zhang, 2020). Currently, the database contains 350 images of CT scans of patients that are positive for COVID-19, and 398 images of CT scans of patients that tested negative.

First, we split the dataset into a training and testing subset; 80% of images were used for training, with the remainder being used for testing. Examples of infected and non-infected CT scans found in our dataset are shown below.



CT Scan of Infected Thoracic Region Marked With COVID-19 Indicator



CT Scan of Non-infected Thoracic Region

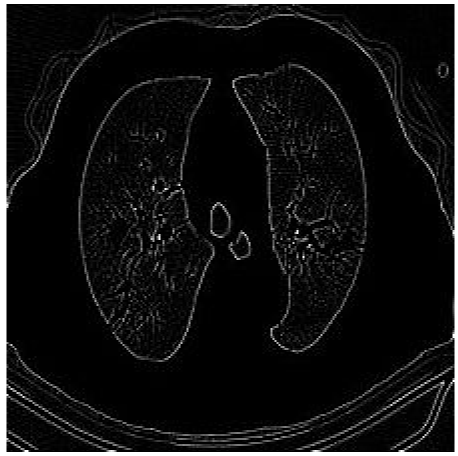
The creators of the dataset at UCSD utilized Densenet-169 in order to produce baseline metrics for COVID-19 diagnosis using CT scans. They achieved relatively high performance in all metrics aside from recall, which was a mere 0.762 (Zhao et al., 2020). Thus, we strove to improve the recall of the network while simultaneously improving or preserving the quality of the other metrics. In order to do this, the Laplace operator was utilized in *Image Preprocessing* below, since it has shown the ability to improve the recall rate of CNNs when tested on X-ray images (Chen, 2019). The Laplacian is primarily used for edge detection, and is defined by $Laplace(f) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$.

Using the original UCSD dataset, we created four new datasets. The first set contained resized images; the second set contained resized and rotated images; the third set had images that underwent the Laplace operator in addition to being resized; and the fourth set had images that received the Laplace operator, in addition to being resized and rotated.

The images in the first dataset were resized to a size of 512x512 pixels via the bicubic interpolation technique, which downscaled the images to a uniform size; this was necessary as the images were previously of variable size and scale. Applying bicubic interpolation minimized image distortion and retained information better than less sophisticated methods such as resizing or cropping and resulted in a smoother image than nearest-neighbors or bilinear interpolation.

The images of the second dataset were also resized to 512x512. In addition, we applied affine transformations of 5°, 10°, 15°, 20°, and 25° to the images in order to increase the size of the dataset by 6 times. This was performed void of the Laplace Operation.

In the third set, we applied the aforementioned Laplacian operator on the images. This operator specializes in finding edges in images by finding discontinuities in brightness. This is beneficial to deep learning models as it accentuates the subtle differences between images, which allows for precise classification.



CT Scan with Laplacian Operator Applied

Our fourth and final dataset contained images in which the aforementioned affine transformations were performed in addition to the application of the Laplace Operator.

CoronaNet

The COVID-19 detection task is a binary classification problem, where the input is an image of a CT scan X and the output is a binary label $y \in \{0, 1\}$ indicating the absence or presence of COVID-19, respectively.

To accomplish this task, a seven-layer CNN was utilized that we dubbed CoronaNet. This model contained two convolution layers, two pooling layers, a flattening layer, and two fully connected dense layers. The dense layers alleviate the vanishing gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the number of parameters. The network structure can be seen in *CoronaNet Layer Map.* Within our model, we utilized Adaptive Moment Estimation (Adam), an adaptive learning rate optimization algorithm, with an initial learning rate of 0.00001. Our activation functions for the intermediate layers was the rectifier function, with the final layer using a sigmoid nonlinearity. A batch size of five was used over 50 epochs, after each of which the model output accuracy, performance metrics (precision, recall, and F1 score), and loss, given by the binary cross-entropy loss function: $L(X, y) = -w_+ \cdot y \log p(Y = 1|X) - w_- \cdot (1-y) \log p(Y = 0|X)$, where p(Y = i|X) is the probability that the network assigns to the label i, $w_+ = |N|/(|P| + |N|)$, and $w_- = |P|/(|P| + |N|)$ with $|P|$ and $|N|$ the number of COVID-19 and NonCOVID-19 CT scans, respectively.

In order to prevent the networks from overfitting, early stopping was performed by saving the network after every epoch and choosing the saved network with the lowest loss on the tuning set. Overall, 2,177,185 parameters were trained and optimized for this task. The architecture of the network can be seen in *Table 9*.

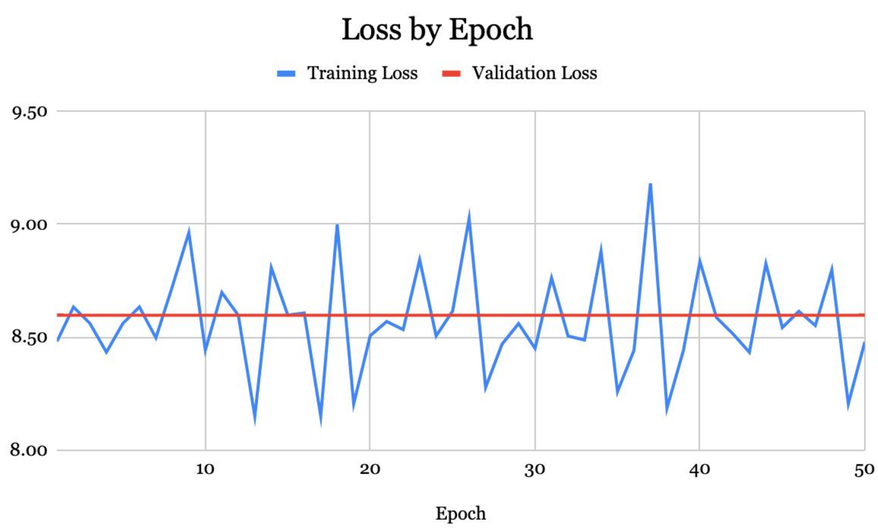
Table 9: CoronaNet Architecture

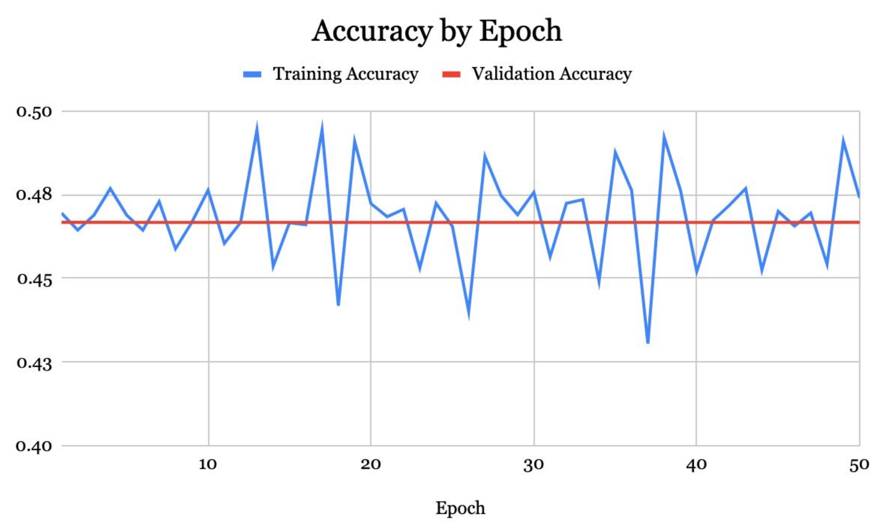
Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 98, 98, 32)	896
Max_pooling2d_1 (MaxPooling2)	(None, 49, 49, 32)	0
conv2d_2 (Conv2D)	(None, 47, 47, 32)	9248
max_pooling2d_2 (MaxPooling2)	(None, 23, 23, 32)	0
flatten_1 (Flatten)	(None, 16928)	0
Dense_1 (Dense)	(None, 128)	2166912
Dense_2 (dense)	(None, 1)	129

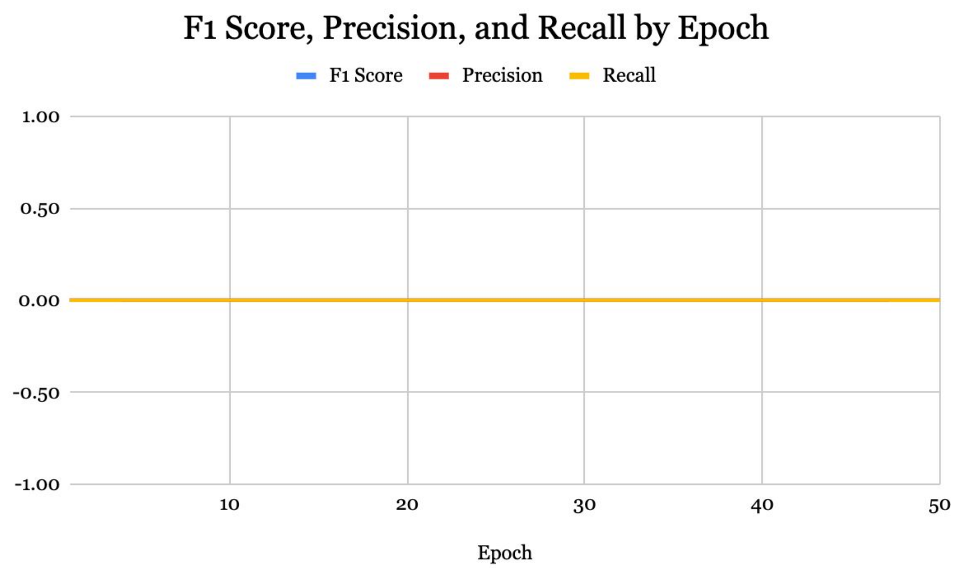
Results

CoronaNet was trained four times, with each iteration using one of the aforementioned datasets.

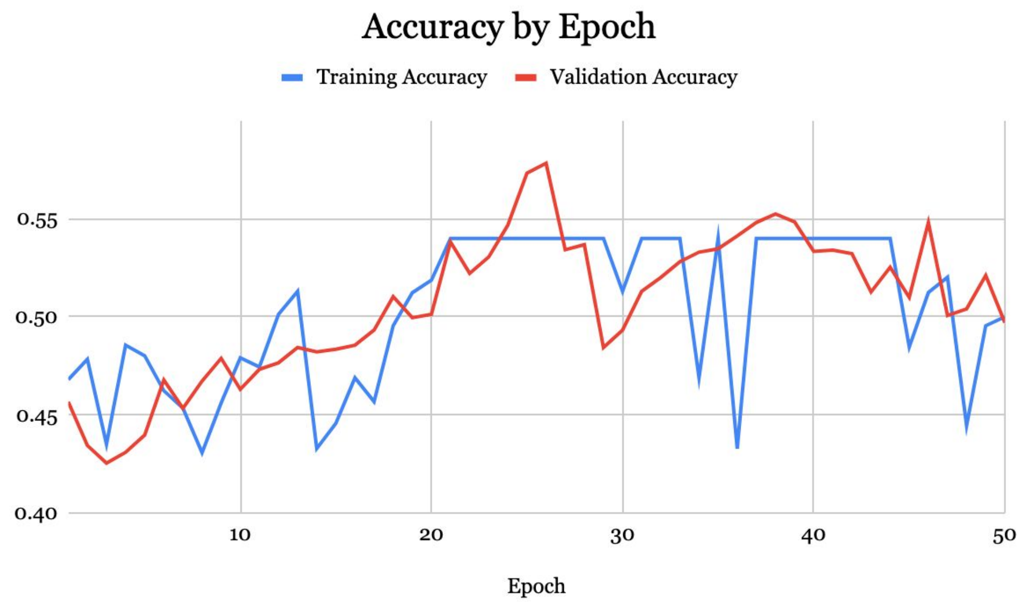
The progression of CoronaNet training on the first dataset can be seen in the figures below. We present loss, accuracy, F1 score, precision, and recall by each epoch.

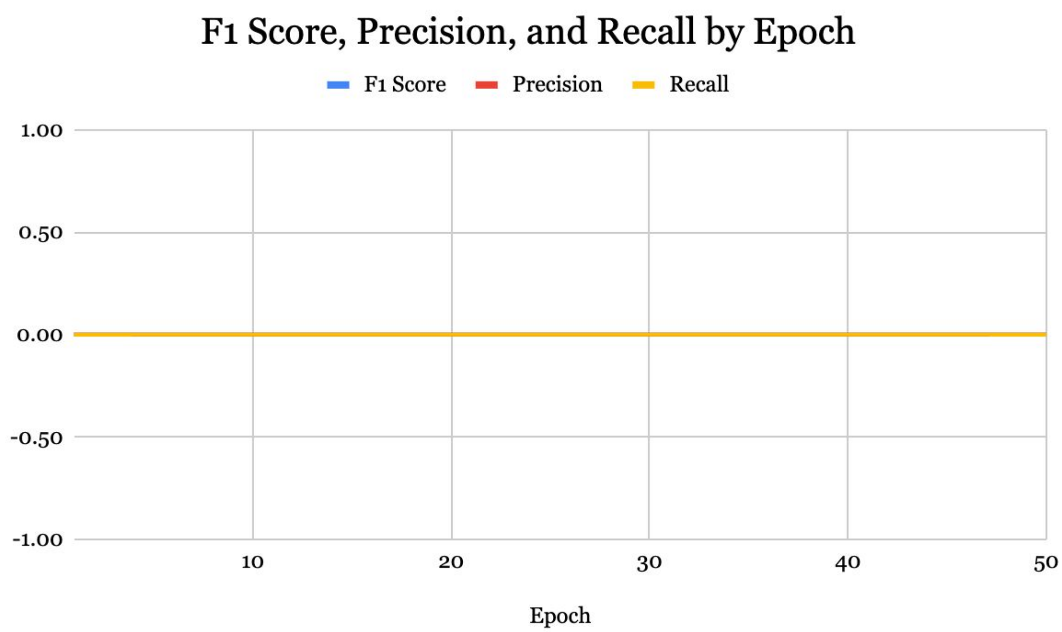




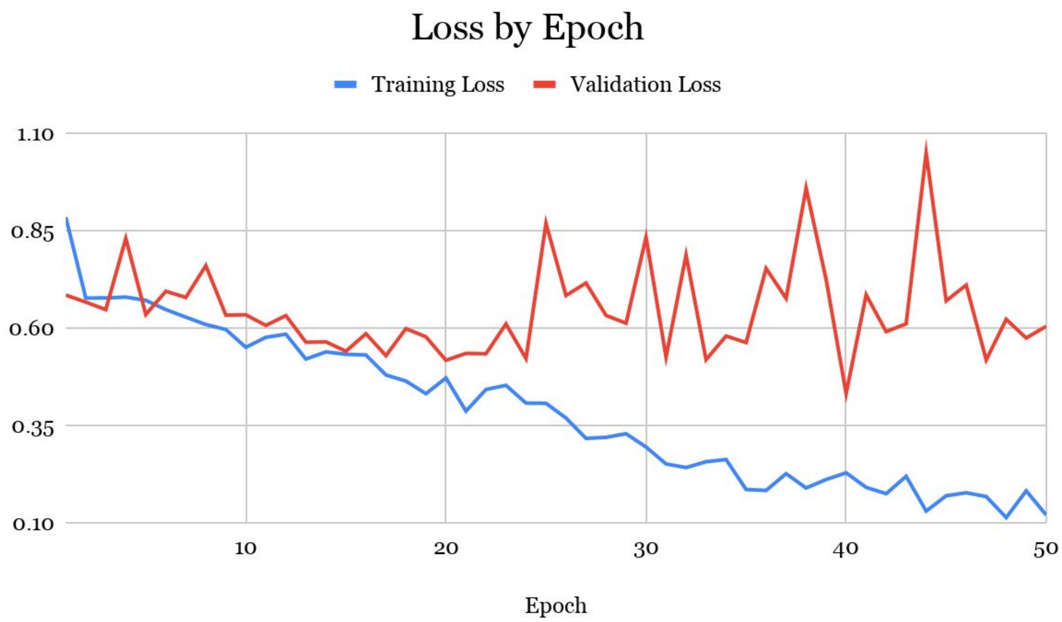


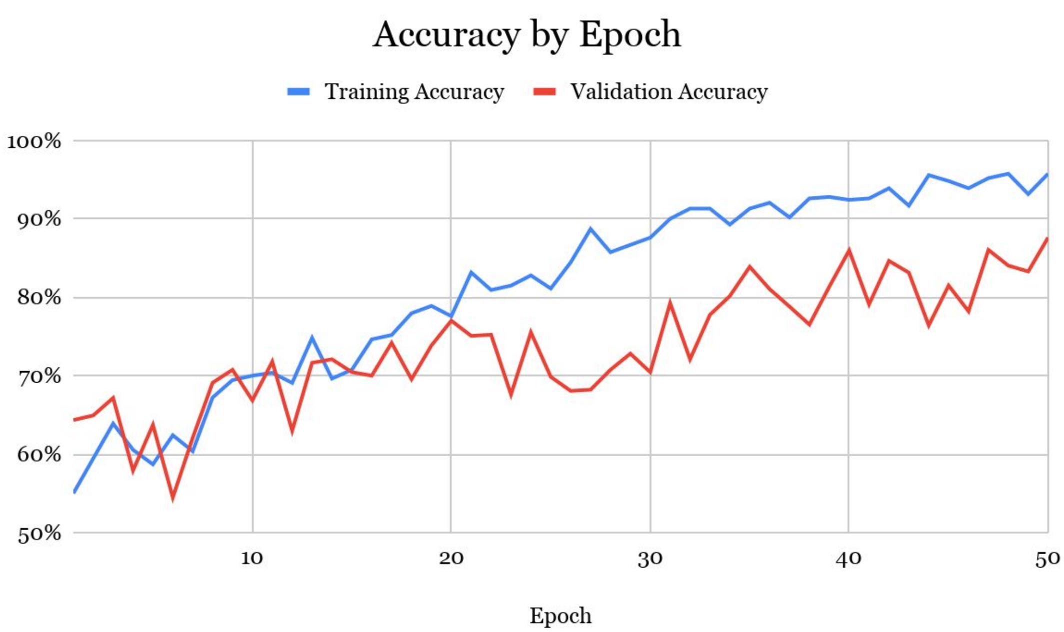
The progression of CoronaNet training on the second dataset can be seen in the figures below. We present loss, accuracy, F1 score, precision, and recall by each epoch.

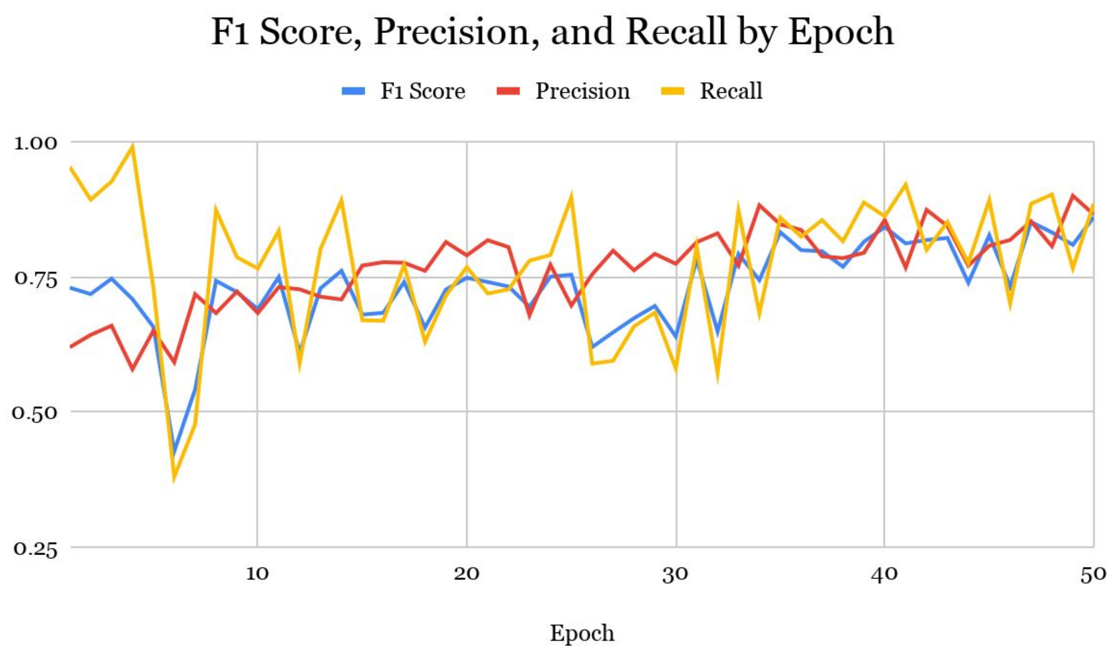

Accuracy by Epoch
Training Accuracy
Validation Accuracy
0.55
0.50
0.45
0.40
10
20
30
40
50
Epoch


F1 Score, Precision, and Recall by Epoch
F1 Score
Precision
Recall
1.00
0.50
0.00
-0.50
-1.00
10
20
30
40
50
Epoch

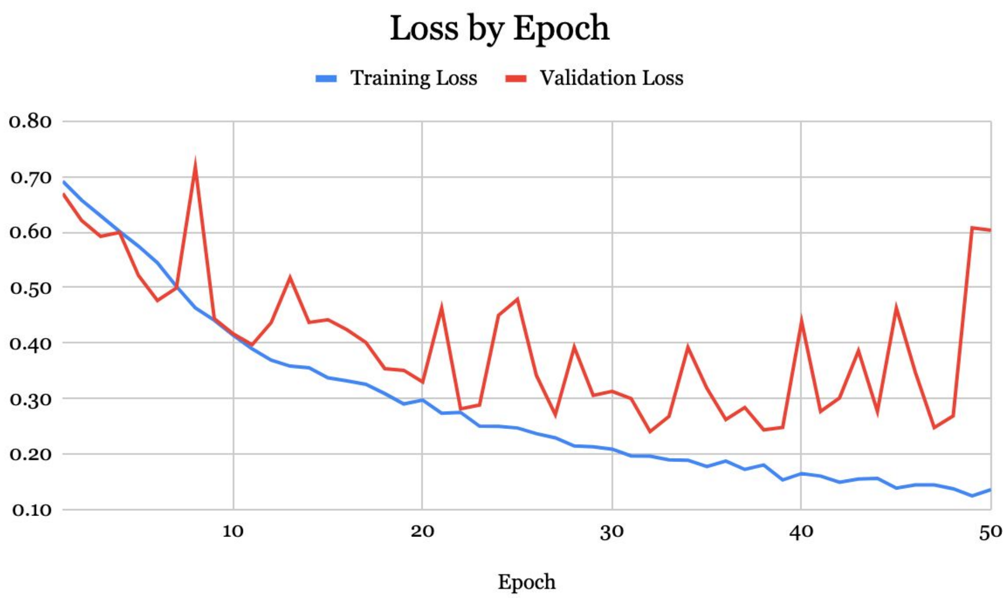
The progression of CoronaNet training on the third dataset can be seen in the figures below. We present loss, accuracy, F1 score, precision, and recall by each epoch.

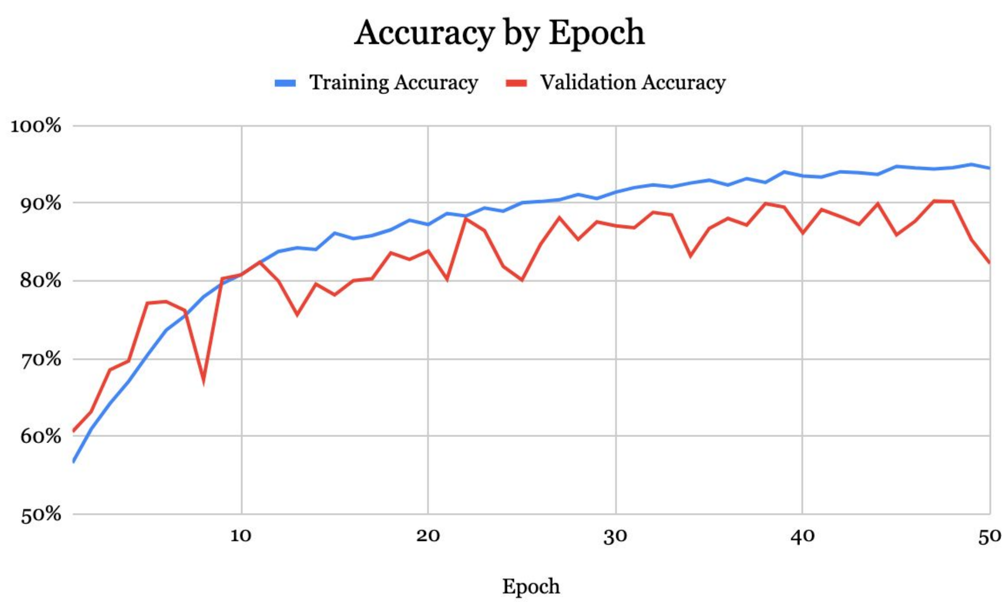


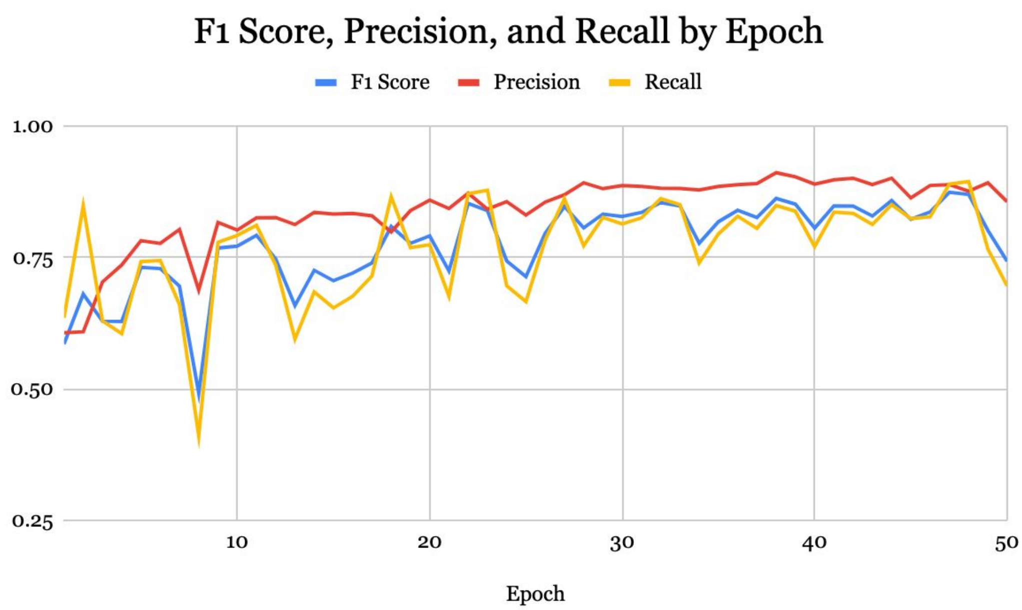



F1 Score, Precision, and Recall by Epoch
F1 Score
Precision
Recall
1.00
0.75
0.50
0.25
10
20
30
40
50
Epoch

The progression of CoronaNet training on the fourth and final dataset can be seen in the figures below. We present loss, accuracy, F1 score, precision, and recall by each epoch.







The peak performance metrics of CoronaNet when trained on the various datasets can be seen in the table below.

Dataset	*Accuracy*	*F1*	*Precision*	*Recall*
1	46.67%	0.0000	0.0000	0.0000
2	57.82%	0.0000	0.0000	0.0000
3	87.61%	0.8601	0.8995	0.9019
4	90.02%	0.8735	0.9028	0.8892

Conclusions

We trained a novel 7-layer CNN called CoronaNet in order to classify images of thoracic CT scans that are infected by COVID-19 using a dataset provided by researchers at UCSD. We strove to specifically improve the recall metric that was subpar in their study by applying a Laplacian Operation to the images. We found that the Laplacian

Operation significantly increased the recall of CoronaNet when compared to the results produced without its application. In fact, we found that the Laplacian Operator significantly improved all of the metrics, including accuracy, F1, precision and recall. Our fourth dataset iteration, in which we rotated and applied the Laplacian Operation to all images, performed the best out of the four that we tested with a peak accuracy of 90.02% and a peak recall of 0.8892. We predict that this is due to the fact that the Laplace Operator highlights key edges within the CT scans that make specific COVID-19 features more distinguishable. Additionally, we noted that when the CoronaNet was trained on unaugmented images, the results were extremely poor, scoring 0 in F1, Precision, and Recall, with a peak accuracy of 46.67% on the first iteration and 57.82% accuracy on the second iteration. The application of the affine transformation also increased performance, as can be seen when comparing the first iteration (no Laplacian Operation or affine transformations) with the second iteration (no Laplacian Operation with affine transformations), and when comparing the third iteration (Laplacian Operation with no affine transformations) and the fourth iteration (Laplacian Operation with affine transformations). The iterations to which the affine transformation was applied resulted in higher performance across the board which is most likely due to an abundance of training data as opposed to the iterations without affine transformation.

CoronaNet produced relatively high metrics in COVID-19 diagnosis through CT scan analysis. This is significant as the traditional diagnosis test, that utilizes RT-PCR, not only takes much longer, but has been shown to be less accurate as well due to its high subjectivity to misdiagnosis by falsely providing a negative test output. We hope that our technology will be able to provide increased diagnostic capabilities in this viral pandemic and provide a foundation to be built off of in the future.

References

Chen, X. (n.d.). Image enhancement effect on the performance of convolutional neural networks. Retrieved from http://www.diva-portal.org/smash/get/diva2:1341096/FULLTEXT02.pdf

Hall, L., Goldgof, D., Paul, R., & Goldgof, G. M. (2020). Finding COVID-19 from Chest X-rays using Deep Learning on a Small Dataset. doi: 10.36227/techrxiv.12083964

Holshue, M. L., Doremalen, N. van, Vaduganathan, M., Fineberg, H. V., & Epidemic Intelligence Service. (2020, March 17). First Case of 2019 Novel Coronavirus in the United States: NEJM. Retrieved from https://www.nejm.org/doi/full/10.1056/NEJMoa2001191

Hurt, B., Kligerman, S., & Hsiao, A. (2020). Deep Learning Localization of Pneumonia. *Journal of Thoracic Imaging*, 1. doi: 10.1097/rti.0000000000000512

Zhao, J., Zhang, Y., He, X., & Xie, P. (n.d.). COVID-CT-Dataset: A CT Scan Dataset about COVID-19. Retrieved from https://arxiv.org/pdf/2003.13865.pdf