

# CoronaNeXt: Evaluating the Performance of the Laplacian Operator in Diagnosing COVID-19 From Chest X-rays

Rohan Bhansali

Senior at Loudoun Academy of Science  
Director at ConnectAI  
Ashburn, United States

Rahul Kumar

Senior at Loudoun Academy of Science  
Director at Aluna Research Group  
Ashburn, United States

**Abstract**— In recent years, usage of deep learning models for medical image classification tasks has grown exponentially due to their state of the art accuracy and efficiency; however, the performance of these models are often limited by insufficient publicly available data. In this study, we continue our previous work in exploring the applications of the Laplace Operator, a detail enhancing image filter, in deep learning models in order to overcome these performance plateaus. Specifically, we evaluate the performance of ResNet-18 in diagnosing COVID-19 from a relatively small dataset of X-ray images. When comparing the performance of our model, dubbed CoronaNeXt, on images without the Laplacian applied to images with the Laplacian applied, we find significant increases in all maximum validation metrics: accuracy improved from 87.6% to 94.8%; F1 score improved from 0.860 to 0.968; specificity improved from 0.865 to 0.944; and sensitivity improved from 0.885 to 0.992. Based on these results, we describe the potential of the Laplacian Operator in drastically improving the performance of deep learning architectures in medical image classification tasks, particularly when utilizing small to medium sized datasets. Notably, sensitivity underwent the most significant improvement, correlating with the results achieved in our previous work using the CT modality. We hope our research will spark further exploration of the Laplace Operator and other derivative-based image preprocessing methodologies in conjunction with powerful deep learning models for medical image tasks.

**Keywords**— COVID-19, Chest X-rays, Laplace Operator, Deep Learning

## I. INTRODUCTION

### A. COVID-19 General Pathology

Coronavirus disease (COVID-19) is a rapidly spreading, respiratory disease that is the cause of a global pandemic at the time of this publication. The disease is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a viral agent that is thought to have originated in a species of bat in the city of Wuhan, China. COVID-19 causes flu-like symptoms, with the vast majority of infected individuals experiencing mild coughing, soreness in the throat, fatigue, and shortness of breath; however, in more severe cases, the virus has led to organ failure, pneumonia, and even death [4]. At the time of publication, 60.3 million cases have been reported globally, with approximately 1.42 million deaths [2].

### B. Respiratory Disease Detection Using X-rays

Since the pandemic's emergence in late 2019, a significant amount of research has been done in utilizing chest X-rays for COVID-19 detection. The disease often presents itself in X-rays in the form of bilateral nodular and peripheral ground glass opacities and consolidation, which refers to dense opacities obscuring vessels and bronchial walls [3].

Convolutional neural networks (CNN) have increasingly been utilized for respiratory disease detection tasks. Recently, researchers used deep CNN models to detect tuberculosis, a bacterial respiratory disease that compromises lung functionality. They report a validation accuracy of 87.1%, significantly higher than the accuracy of experienced radiologists [9]. Another group reported state of the art sensitivity, specificity, and accuracy metrics in the COVID-19 detection task using a relatively large chest X-ray dataset, from which achieved a mean accuracy of 98% [7]. These experiments, and many others, demonstrate the strong potential for the usage of deep CNNs in the classification of thoracic medical images.

### C. Residual Neural Networks

In this study, we utilize ResNet-18 for the COVID-19 classification. ResNet-18 is an 18 layer, deep residual network. Residual networks are named based on the concept of residual functions, in which the layers of the network learn by utilizing layer inputs rather than learning unfamiliar functions [6]. Residual neural networks have shown the ability to be computationally efficient while achieving state of the art metrics on various image related tasks.

### D. Laplacian Filter Intuition

The Laplacian Filter, otherwise known as the Laplace Operator, is a second derivative based image enhancement method and is mathematically displayed in Fig. 1. It has been extensively noted as being efficient at highlighting fine details in images, specifically marking parts of an image where there are rapid shifts in intensity. The filter operates on an image by summing the differences of intensity values of neighboring pixels to replace the value of a singular pixel. As a result, pixels at which the surrounding gradient change is most drastic will be highlighted [5]. In practice, the Laplacian Filter highlights bright

edges to a greater extent than they are displayed in unfiltered images.

$$\text{Laplace}(f) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

Fig. 1. Laplacian Operator formula

### E. Deep Learning Applications of the Laplacian Filter

The ability of the Laplacian Filter to highlight regions of major gradient shift makes it useful when used in conjunction with CNNs, as it makes features more easily detectable. Specifically, the Laplace Operator was first noted as leading to significant performance improvements in the CNNs in an experiment that utilized the filter to improve the ability of a Faster R-CNN in detecting pedestrians by improving image quality; they reported significant increases in precision and recall ability of the CNN [12]. In our previous study, we applied the Laplacian Operator to a small CT scan dataset and reported significant improvements across all metrics, with minimal overfitting [1]. In this study, we further explore the usage of the Laplacian Operator in medical image classification tasks by using it in conjunction with a commonly used deep learning architecture, ResNet-18, on the X-ray modality for COVID-19 detection.

## II. METHODS

### A. Dataset

First, we created a suitable dataset of chest X-rays that we could use for training and validation purposes. Specifically, we combined a dataset published by the Université de Montréal with another dataset published by the National Institutes of Health, providing us with a total of 11,094 chest X-rays, of which 4,498 were COVID-19 positive and 6,596 were COVID-19 negative [7]. A sample collection of these X-rays is shown in Fig. 2.

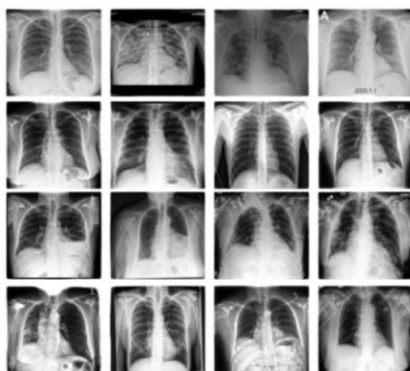


Fig. 2. Top two rows are COVID-19 positive X-rays; bottom two rows are COVID-19 negative X-rays

As Fig. 2 depicts, the X-rays in the combined dataset were all of variable size and shape. Consequently, it was necessary to conduct multiple pre-processing steps before our images were in a usable form for model training.

### B. Image Resizing

We first sought to transform all of the X-ray images in the combined dataset to a uniform size of 512x512 pixels. In order to do so, we utilized nearest-neighbors interpolation, a computationally efficient image scaling technique that allows images to be resized to custom scale with minimal distortion by replacing the magnitude of pixels with the magnitudes of its neighboring pixels. This method allows important information in the image to be maintained, such as the location of opacities of consolidation that are indicative of COVID-19.

### C. Applying the Laplacian Operator

Building on our previous work, in which we applied the Laplace Operator to CT scans, we created a second dataset, the “Laplaced” dataset, containing the same images from the initial dataset, the “non-Laplaced” dataset; however, these images were processed with the Laplace Operator [1]. A sample chest X-ray can be seen in Fig. 3; when the Laplacian Filter is applied, the resulting image is seen in Fig. 4. Although faint, the contour lines and other sharp gradient shifts of the X-ray shown Fig. 3 are accentuated in Fig. 4.



Fig. 3. Chest X-ray image before Laplacian filter was applied



Fig. 4. Chest X-ray image after Laplacian filter was applied

### D. Dataset Split

After the images in both the “non-Laplaced” and “Laplaced” datasets had been fully processed, we split them each into two subsets: a training set and a validation set, with 75% of the images being placed in the former and the remaining 25% being placed in the latter. We utilized the training set for the training of our model and the validation test to subsequently test our model’s performance.

### E. Model

We chose to approach the diagnosis of COVID-19 as a binary classification problem, where the inputted chest X-ray corresponded to an outputted binary label signifying that COVID-19 was absent or present within the X-ray. Accordingly, we utilized the eighteen-layer deep convolutional

neural network structure in ResNet-18. Residual networks such as ResNet are useful because they enable an increase in network depth while minimizing the downsides commonly associated with doing so, including longer training time, decreased efficiency caused by additional parameters, and the vanishing gradient problem [6]. We trained our model, dubbed CoronaNeXt, over ten epochs with a batch size of ten images, initial learning rate of 0.0001, and binary cross entropy loss function to optimize 11,511,784 parameters. Between layers, our model used the rectifier activation function with the final layer using the sigmoid activation function.

### III. RESULTS

To create a baseline for comparison purposes, we first trained CoronaNeXt on the “non-Laplaced” dataset which contained images that did not have the Laplace Operator performed on them. Subsequently, we repeated an identical process, this time on the “Laplaced” dataset. We acquired the results shown in Table 1.

TABLE I.

	Accuracy	F1 Score	Specificity	Sensitivity
<i>Non-Laplaced dataset</i>	87.6%	0.860	0.865	0.885
<i>Laplaced dataset</i>	94.8%	0.968	0.944	0.992

Figs. 5, 6, 7, and 8 demonstrate CoronaNeXt’s improvement in the accuracy, F1 score, specificity, and sensitivity metrics between the “non-Laplaced” to the “Laplaced” dataset.

Accuracy by Epoch

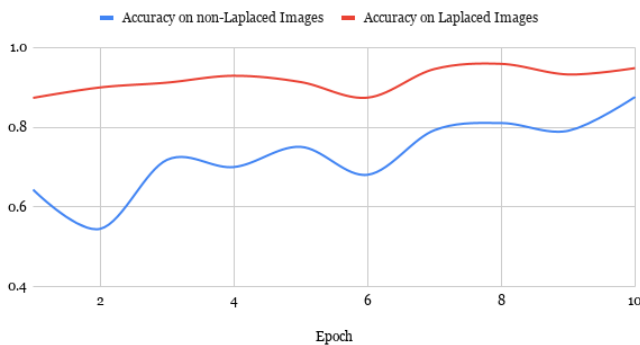


Fig. 5. Comparison of accuracy by epoch on non-Laplaced and Laplaced images

F1 Score by Epoch

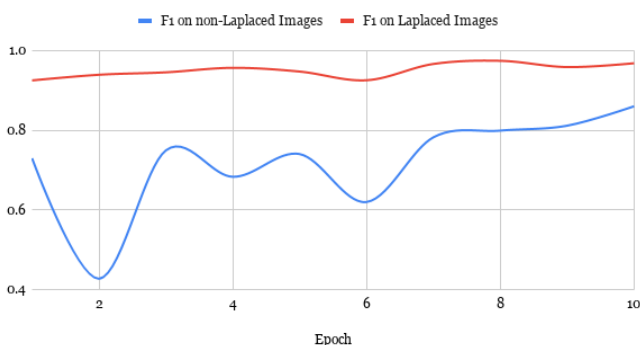


Fig. 6. Comparison of F1 score by epoch on non-Laplaced and Laplaced images

Specificity by Epoch

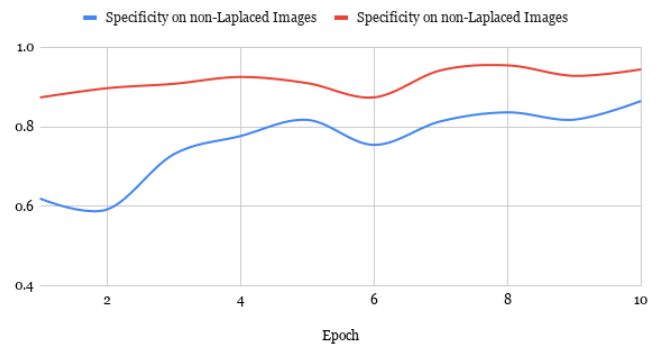


Fig. 7. Comparison of specificity by epoch on non-Laplaced and Laplaced images

Sensitivity by Epoch

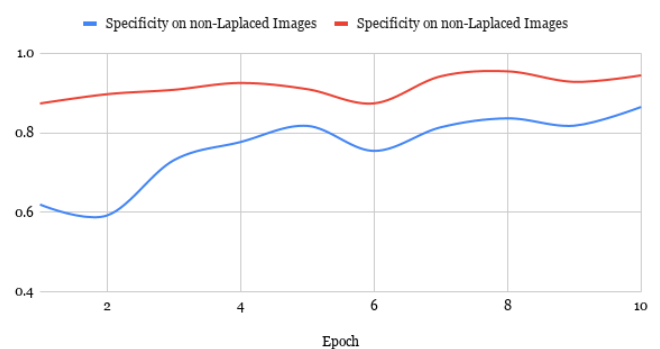


Fig. 8. Comparison of sensitivity by epoch on non-Laplaced and Laplaced images

### IV. CONCLUSION

In this study, we determined the performance of a ResNet-18 on the COVID-19 classification task in chest X-rays when the Laplacian Filter was applied. The results recorded in this experiment support the findings displayed in our previous work [1]. Specifically, we report that when the Laplace Filter is utilized, improvements in all recorded maximum validation metrics can be seen: F1 score improved from 0.860 to 0.968; specificity improved from 0.865 to 0.944; and sensitivity improved from 0.885 to 0.992. These results signal the high efficiency of the Laplacian Filter in improving the performance of deep neural networks on the X-ray modality for the COVID-19 diagnosis task. The improvements in performance can be attributed to the ability of Laplacian Filter to drastically improve key feature differentiation by highlighting pivotal regions of gradient shifts. As previously established, these regions are often indicative of abnormalities that can reveal the presence of COVID-19 or other respiratory diseases.

We verify the Laplacian Filter’s potential in positively impacting the classification ability of deep neural networks across various image modalities. Our findings, both in this study and our preceding study, solidify the justification for greater exploration into the Laplacian Filter’s vast applications in medical imaging tasks when small or medium sized datasets are available, as is often the case.

REFERENCES

- [1] Bhansali, R., Kumar, R., & Writer, D. (2020). CoronaNet: A Novel Deep Learning Model for COVID-19 Detection in CT Scans. *Journal of Student Research*, 9(2). <https://doi.org/10.47611/jsrhs.v9i2.1246>
- [2] COVID-19 United States Cases by County. Johns Hopkins Coronavirus Resource Center. <https://coronavirus.jhu.edu/us-map>.
- [3] Kong, W., & Agarwal, P. P. (2020). Chest Imaging Appearance of COVID-19 Infection. *Radiology: Cardiothoracic Imaging*, 2(1). <https://doi.org/10.1148/ryct.2020200028>
- [4] Lai, C. C., Shih, T. P., Ko, W. C., Tang, H. J., & Hsueh, P. R. (2020). Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and coronavirus disease-2019 (COVID-19): The epidemic and the challenges. *International journal of antimicrobial agents*, 55(3), 105924. <https://doi.org/10.1016/j.ijantimicag.2020.105924>
- [5] Laplacian Filter. Laplacian Filter - an overview | ScienceDirect Topics. <https://www.sciencedirect.com/topics/engineering/laplacian-filter>.
- [6] Li, Y., Zhang, Y., Xu, Y., Miao, Z., & Li, H. (2017). Does ResNet Learn Good General Purpose Features? *AIACT '17: Proceedings of the 2017 International Conference on Artificial Intelligence, Automation and Control Technologies*, 1–5. <https://doi.org/10.1145/3080845.3080864>
- [7] Minaee, S., Kafieh, R., Sonka, M., Yazdani, S., & Soufi, G. J. (2020). Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning. *Medical Image Analysis*, 65, 101794. <https://doi.org/10.1016/j.media.2020.101794>
- [8] Napolitano, P., Piccoli, F., & Schettini, R. (2018). Anomaly Detection in Nanofibrous Materials by CNN-Based Self-Similarity. *Sensors*, 18(1). <https://doi.org/10.3390/s18010209>
- [9] Oloko-Oba, M., & Viriri, S. (2020). Diagnosing Tuberculosis Using Deep Convolutional Neural Network. *Lecture Notes in Computer Science Image and Signal Processing*, 151–161. [https://doi.org/10.1007/978-3-030-51935-3\\_16](https://doi.org/10.1007/978-3-030-51935-3_16)
- [10] Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020). Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in Biology and Medicine*, 121, 103792. <https://doi.org/10.1016/j.compbiomed.2020.103792>
- [11] Sekeroglu, B., & Ozsahin, I. (2020). Detection of COVID-19 from Chest X-Ray Images Using Convolutional Neural Networks. *SLAS Technology*, 25(6), 553–565. <https://doi.org/10.1177/2472630320958376>
- [12] Q. Tian, G. Xie, Y. Wang and Y. Zhang, "Pedestrian Detection Based on Laplace Operator Image Enhancement Algorithm and Faster R-CNN," 2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Beijing, China, 2018, pp. 1-5. <https://doi.org/10.1109/CISP-BMEI.2018.8633093>