PulmXNet: A Novel Deep Learning Architecture for the Diagnosis of COVID-19 Alongside Other Respiratory Illnesses (Bacteria and Viral Pneumonia, Tuberculosis) from Chest X-rays

Justin Shen[1] and Davesh Valagolam[1]

[1i, 1ii]Jericho Senior High School, 99 Cedar Swamp Rd, Jericho, NY 11753

***Abstract*—The novel coronavirus (COVID-19) has brought tremendous international detriment as it has forced the world into a global pandemic and shutdown. COVID-19 and other respiratory illnesses directly impact the pulmonary tract of the human body, leading to noticeable structural differences which can be identified via a chest x-ray (CXR). This study highlights the implementation of a novel convolutional neural network (CNN) in the diagnosis of 5-classes of CXRs (normal, COVID-19, tuberculosis, bacterial and viral pneumonia). This model was trained over 17 epochs and had 3,403,061 parameters. The overall 5-class accuracy for PulmXNet was 86.24%. The individual accuracy values for normal, COVID-19, tuberculosis, and bacterial and viral pneumonia were 85.59%, 85.45%, 84.16%, 89.33%, and 85.52%, respectively. This model was the first 5-Class CNN model to classify for normal, COVID-19, tuberculosis, bacterial and viral pneumonia CXRs and was able to maintain a relatively high accuracy and low parameters, demonstrating computational efficiency. Future investigations should look to further optimize this model with Bayesian or random search optimizations.**

I. Introduction

The novel coronavirus (COVID-19) first surfaced in Wuhan, China in December 2019, later escalating to global pandemic status prompting warranted concern from governmental and healthcare officials [2].

As COVID-19 directly impacts the respiratory tract, clear morphological abnormalities can be noticed in chest x-rays (CXRs) [3]. Similar morphological abnormalities are present in other respiratory illnesses such as pneumonia and tuberculosis allowing for their diagnosis through CXRs as well [3].

However, the main limitation with radiology-aided diagnosis is the high cost associated with the use of trained clinical radiologists. As a result, with the advancement of recent deep learning methodologies, prior research has identified the merit of using a hybrid radiology-deep learning methodology to diagnose respiratory illnesses (COVID-19, pneumonia, tuberculosis) [4]. These procedures can often be cheaper as well as more accurate than traditional radiological practices. Already, certain deep learning architectures have outperformed average radiologist performance [4].

Therefore, the purpose of this research was to construct a novel convolutional neural network architecture (PulmXNet), the first unified 5-class convolutional neural network (CNN) for the diagnosis of normal, COVID-19, tuberculosis, and bacterial and viral pneumonia. A 5-class model for respiratory illness diagnosis is crucial for its potential clinical applicability as the overlapping symptomologies of these illnesses can create difficulties for accurate diagnosis.

II. Methods

The data for COVID-19 and normal CXRs was sourced from Kaggle databases, the pneumonia CXRs were from the Mendeley dataset, and the tuberculosis CXRs were from the National Institutes of Health National Library of Medicine database [5,6,7]. The training to testing data ratio was 3:1 and the data was sheared, rotated, and scaled to increase noise and prevent training bias (Table 1). To limit PulmXNet's overemphasis on average accuracy metrics, only 300 images were tested from the bacterial pneumonia class.

TABLE I. DISTRIBUTION OF THE DATA USED IN PULMXNET

Data Type	Disease Class				
	Normal	*COVID-19*	*Bacterial Pneumonia*	*Viral Pneumonia*	*Tuberculosis*
Train	1006	164	2472	1120	293
Test	225	55	300	373	101

The images were scaled to 250px by 250px to reduce training parameters. The architecture consisted of 3 convolutional layers and 128 nodes for the neural network layer. The rectifier function was used between these layers and softmax was used to predict the output. The 5-class PulmXNet was trained over 17 epochs and had 3,403,061 parameters.

$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \quad (1)$$

$$CE = -\sum_i^C t_i \log(f(s)_i) \quad (2)$$

The equation for softmax (1) predicts the probability of each type of disease based on the artificial neural network layer. Categorical cross entropy loss was calculated as a measure to determine the model's improvement on a finer scale. Loss is a more reliable measure for training as it determines more than simply the right and wrong about the prediction but details the degree to which the prediction was off (2).

The accuracy for the model was calculated to determine the effectiveness of the model. The precision is the straight average of the diseases removing any dataset biases. The recall is the true positive rate. The F1 score is a summary statistic that factors in both precision and recall.

III. Results and Discussion

TABLE II. ACCURACY METRICS FOR 5-CLASS PULMXNET

Disease Class	*Accuracy*	*Precision*	*Recall*	*F1 Score*
Normal	85.59%	85.59%	95.96%	90.48%
COVID-19	85.45%	85.45%	90.39%	87.85%
Bacterial Pneumonia	89.33%	89.33%	83.49%	86.31%
Viral Pneumonia	85.52%	85.52%	87.16%	86.33%
Tuberculosis	84.16%	84.16%	74.56%	79.07%

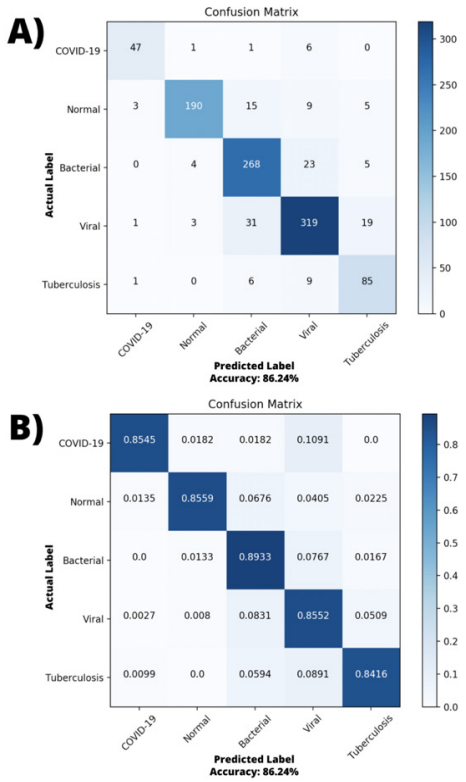

Figure 1. Confusion Matrices for PulmXNet. A) Non-normalized Confusion Matrix for 5-Class PulmXNet. B) Normalized Confusion Matrix for 5-Class PulmXNet.

The 5-class PulmXNet model distinguished between COVID-19, Normal, Bacterial, Viral, and Tuberculosis CXRs. Table 2 shows a summary of the performance metrics for the PulmXNet model. This model yielded an overall accuracy of 86.24% (Figure 1). The accuracy and precision values for normal, COVID-19, tuberculosis, and bacterial and viral pneumonia were 85.59%, 85.45%, 84.16%, 89.33%, and 85.52%, respectively (Table 2) . F1 scores were highest for the normal class (90.48%) and the lowest for the tuberculosis class (79.07%) (Table 2), which could be attributed to the low number of testing images compared to other classes.

This is the first proposed unified 5-class model for the classification of CXRs with the COVID-19 class. The PulmXNet model is also one of the first COVID-19 models to have a custom architecture without relying on pre-trained, generic convolutional layers, such as VGG-19 and ResNet. The model was manually trained to minimize the number of parameters for computational efficiency, while maximizing accuracy. With only 3,403,061 parameters, the 5-class PulmXNet model is far less than any of the current 4-class models which have a minimum of 9.4 million parameters [8]. In fact, PulmXNet has lower parameters for all 2-class and 3-class models, with the exception of the DarkNet model studied by Ozturk et. al [9].

IV. Conclusions

The widespread nature of x-ray imaging technology coupled with deep-learning models provides promise for cheaper radiological practices into the future. This research highlights the construction of the first unified CNN architecture that classifies CXRs for the following classes: healthy, COVID-19, tuberculosis, bacterial and viral pneumonia. By constructing PulmXNet's architecture from scratch, its use was optimized for chest x-ray diagnosis, unlike existing models in literature. Future investigations should optimize PulmXNet via Bayesian and random search optimization.

V. Acknowledgment

The authors of this paper would like to acknowledge the unconditional support from Dr. Serena McCalla and Dr. Jean-François Daneault. The authors would also like to thank the studies which compiled the data used in this experiment.

VI. References

[1] H. Li, S.-M. Liu, X.-H. Yu, S.-L. Tang, and C.-K. Tang, "Coronavirus disease 2019 (COVID-19): current status and future perspectives," International Journal of Antimicrobial Agents, vol. 55, no. 5, p. 105951, 2020.

[2] Y.-C. Liu, R.-L. Kuo, and S.-R. Shih, "COVID-19: The first documented coronavirus pandemic in history," Biomedical Journal, 2020.

[3] H. Chen, L. Ai, H. Lu, and H. Li, "Clinical and imaging features of COVID-19," Radiology of Infectious Diseases, Apr. 2020.

[4] A. I. Khan, J. L. Shah, and M. M. Bhat, "CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images," Computer Methods and Programs in Biomedicine, vol. 196, p. 105581, 2020.

[5] M. E. H. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, K. R. Islam, M. S. Khan, A. Iqbal, N. Al-Emadi, M. B. I. Reaz, and M. T. Islam, "Can AI help in screening Viral and COVID-19 pneumonia?," IEEE Access, pp. 1–1, 2020.

[6] D. S. Kermany, M. Goldbaum, W. Cai, C. C. Valentim, H. Liang, S. L. Baxter, A. Mckeown, G. Yang, X. Wu, F. Yan, J. Dong, M. K. Prasadha, J. Pei, M. Y. Ting, J. Zhu, C. Li, S. Hewett, J. Dong, I. Ziyar, A. Shi, R. Zhang, L. Zheng, R. Hou, W. Shi, X. Fu, Y. Duan, V. A. Huu, C. Wen, E. D. Zhang, C. L. Zhang, O. Li, X. Wang, M. A. Singer, X. Sun, J. Xu, A. Tafreshi, M. A. Lewis, H. Xia, and K. Zhang, "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," Cell, vol. 172, no. 5, 2018.

[7] S. Jaeger, S. Candemir, S. Antani, Y.-X. J. Wáng, P.-X. Lu, and G. Thoma, "Two public chest X-ray datasets for computer-aided screening of pulmonary diseases," Quantitative Imaging in Medicine and Surgery, vol. 4, no. 6, pp. 475–477, Dec. 2014.

[8] Y. Oh, S. Park, and J. C. Ye, "Deep Learning COVID-19 Features on CXR using Limited Training Data Sets," IEEE Transactions on Medical Imaging, 2020.

[9] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images," Computers in Biology and Medicine, vol. 121, p. 103792, 2020.