Lung Disease Clasification - Applied Artificial Intelligence Project

Anonymous COMP6721 submission

Paper ID Group-Q

1. Problem Statement and Application

The destruction caused by COVID-19 created a need for diagnosis that is reliable and fast [21]. Chest X-ray acquisition is easy but needs to be evaluated by expert radiologists [15]. We propose that a deep CNN model can help diagnose new diseases much faster and accurately. We plan to create models that will classify multiple lung diseases like COVID-19 and Atelectasis. This will allow us to reduce the turn-around-times for diagnosis of new diseases. There are a number of challenges that we foresee, the datasets are highly imbalanced so we will have to take corrective measures. Images from different X-Ray scanners have different radiographic contrast [13] this could have a negative impact on our model's results. We will try different models to solve this problem and present a detailed comparison of the results. After evaluating the results, we will choose the best model in terms of both efficiency and accuracy.

Our novelty will be producing an explainable model as well as a custom CNN that we plan to create which could get us better results than the existing architectures. We plan on releasing the best performing model, trained on all images to serve as the base model for other problems.

2. Image Dataset Selection

We chose chest X-Ray datasets (Tab. 1) that have varying disease types to ensure that our models are robust. The main concern while selecting the datasets was the number of images per class as most datasets were highly skewed. We rejected datasets where the images were compressed and noisy as this can lead to mis-diagnosis [18]. This will help reduce the time spent in the pre-processing stage.

Dataset	No. of Images	Classes	Image Size
Pneumonia, COVID-19 [16] [4] [5]	10,192 (Normal) + 3,616 (COVID-19) + 1,345 (Pneumonia)	3	299 x 299
Pneumonia [11] [20]	1,583 (Normal) + 1,493 (Viral Pneumonia) + 2,780 (Baterial Pneumonia)	3	224 x 224
Chest X-Ray8 [22] [23]	60,190 (Normal) + 16,610 (Infiltration) + 8,284 (Atelectasis)	3	1024 x 1024

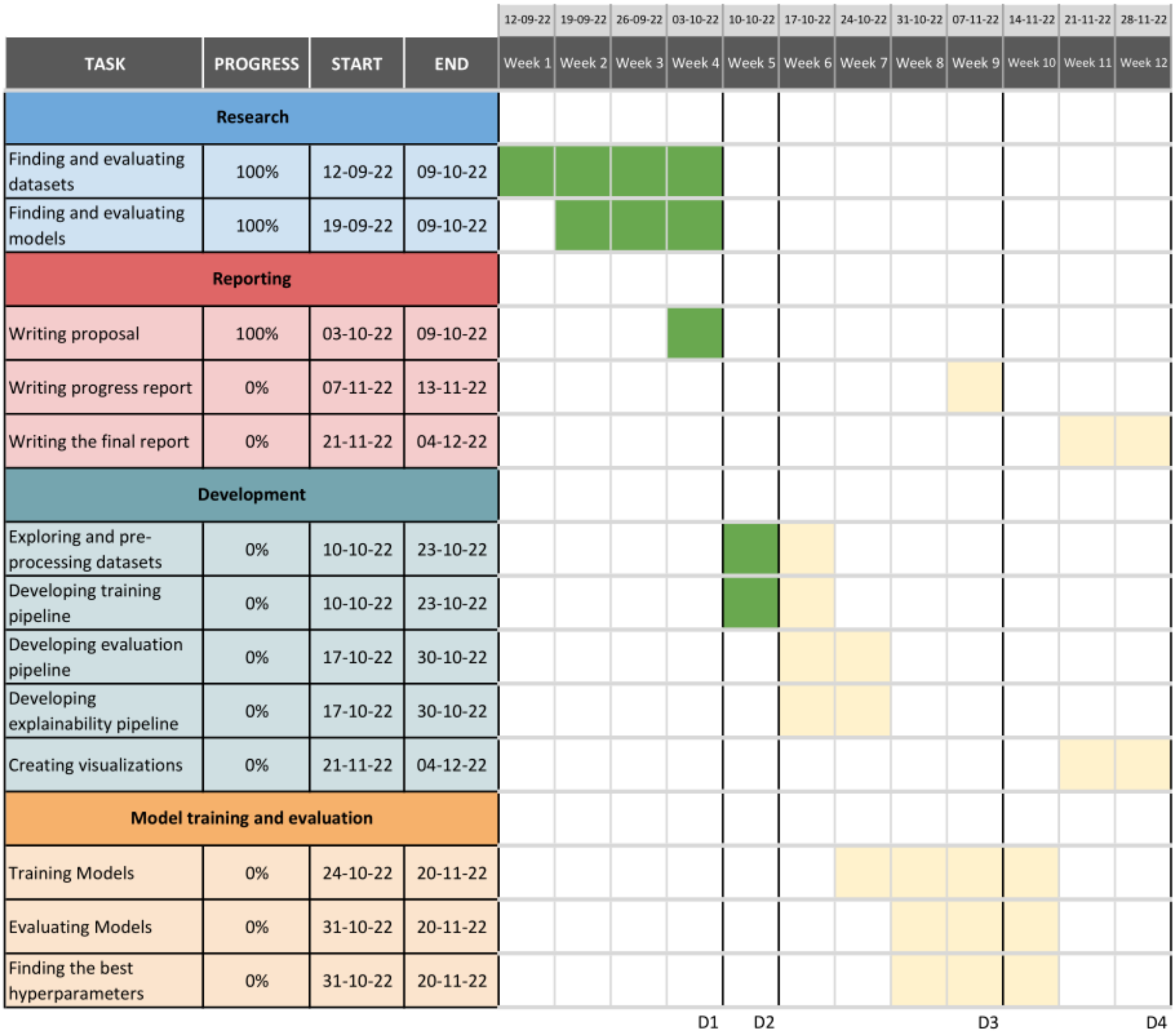
Table 1. Shortlisted Datasets.

3. Possible Methodology

As our datasets are from different sources, we will explore different pre-processing techniques like histogram equalization and Gaussian blur [6] in PyTorch using functions like normalize and gaussian_blur [14] to make training easier for our CNN. We will explore several neural network architectures like VGG 16 [17], Inception V3 [19], Resnet [9], and produce our own Custom CNN model as well with different depth, size of kernel, strides and types of layers. To train our models, we will use cross-entropy loss and experiment with optimizers [8] like Stochastic Gradient Descent, Adam, AdaDelta [10] etc. to select the optimizer that gives us a lower loss with less epochs. To ensure that our model does not get stuck at a local minima, we will try different learning rate decay methods. While training, we will tweak different hyperparameters like epoch, activation functions, and batch size to ensure that we get a well performing model. As the size of our dataset is small, we plan on experimenting with data augmentation using techniques like changing contrast and image flipping as well as transfer learning to improve our results. To find the best hyperparameters, we will perform ablation studies and try to make use of Bayesian hyperparameter optimization [1].

Given that our datasets are highly imbalanced, we will try to use class weights and data augmentation for minority class [2]. For evaluation, we will explore different metrics like confusion matrix, ROC Curve and F-Measure [3]. We will also consider the FLOPs of our models as one of the key metrics. To explain the results of our models, we plan on using SHAP [12] and GradCAM [7] which will help us diagnose our models and also help end users gain more confidence in our model's decisions.

COMP6721
#Group-Q



Deliverables:	
Proposal Submission Date: 09-10-22	D1
Proposal Revision Date: 16-10-22	D2
Progress Report Submission Date: 13-11-22	D3
Final Report, Presentation and Code Submission Date: 04-12-22	D4

Figure 1. The Gantt chart above portrays how our project will progress. The deliverables have been mentioned as well. We will work prarallely on different parts of the project as shown in the gantt chart. Different team members will work on different tasks like building the ML pipeline and building the data pre-processing pipeline at the same time. After the deveopment and training is complete, we will take up different sections of the final report and presentation to complete it in time for the final submission on 04-12-22.

References

[1] Maximilian Balandat, Brian Karrer, Daniel R. Jiang, Samuel Daulton, Benjamin Letham, Andrew Gordon Wilson, and Eytan Bakshy. BoTorch: A Framework for Efficient Monte-Carlo Bayesian Optimization. In *Advances in Neural Information Processing Systems 33*, 2020. 1

[2] Aditya Bhattacharya. How to use smote for dealing with imbalanced image dataset for solving classification problems. https://medium.com/swlh/how-to-use-smote-for-dealing-with-imbalanced-image-dataset-for-solving-classification-problems-3aba7d2b9cad, 2020. 1

[3] Jason Brownlee. A gentle introduction to the fbeta-measure for machine learning. https://machinelearningmastery.com/fbeta-measure-for-machine-learning/, 2020. 1

[4] Muhammad E. H. Chowdhury, Tawsifur Rahman, Amith Khandakar, Rashid Mazhar, Muhammad Abdul Kadir, Zaid Bin Mahbub, Khandakar Reajul Islam, Muhammad Salman Khan, Atif Iqbal, Nasser Al Emadi, Mamun Bin Ibne Reaz, and Mohammad Tariqul Islam. Can ai help in screening viral and covid-19 pneumonia? *IEEE Access*, 8:132665–132676, 2020. 1

[5] Muhammad E. H. Chowdhury, Tawsifur Rahman, Amith Khandakar, Rashid Mazhar, Muhammad Abdul Kadir, Zaid Bin Mahbub, Khandakar Reajul Islam, Muhammad Salman Khan, Atif Iqbal, Nasser Al Emadi, Mamun Bin Ibne Reaz, and Mohammad Tariqul Islam. Covid-19 radiography database. https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database, 2021. 1

[6] Agata Giełczyk, Anna Marciniak, Martyna Tarczewska, and Zbigniew Lutowski. Pre-processing methods in chest x-ray image classification. *Plos one*, 17(4):e0265949, 2022. 1

[7] Jacob Gildenblat and contributors. Pytorch library for cam methods. https://github.com/jacobgil/pytorch-grad-cam, 2021. 1

[8] Ayush Gupta. A comprehensive guide on deep learning optimizers. https://www.analyticsvidhya.com/blog/2021/10/a-comprehensive-guide-on-deep-learning-optimizers/, 2021. 1

[9] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016. 1

[10] Ibrahem Kandel, Mauro Castelli, and Aleš Popovič. Comparative study of first order optimizers for image classification using convolutional neural networks on histopathology images. *Journal of imaging*, 6(9):92, 2020. 1

[11] Daniel Kermany, Kang Zhang, Michael Goldbaum, et al. Labeled optical coherence tomography (oct) and chest x-ray images for classification. *Mendeley data*, 2(2), 2018. 1

[12] Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017. 1

[13] Andrew Murphy. Radiographic contrast. https://radiopaedia.org/articles/radiographic-contrast, 2022. 1

[14] PyTorch. Transforming and augmenting images. https://pytorch.org/vision/stable/transforms.html. 1

[15] Inc. (RSNA) Radiological Society of North America. Chest x-ray. https://www.radiologyinfo.org/en/info/chestrad, 2020. 1

[16] Tawsifur Rahman, Amith Khandakar, Yazan Qiblawey, Anas Tahir, Serkan Kiranyaz, Saad Bin Abul Kashem, Mohammad Tariqul Islam, Somaya Al Maadeed, Susu M. Zughaier, Muhammad Salman Khan, and Muhammad E.H. Chowdhury. Exploring the effect of image enhancement techniques on covid-19 detection using chest x-ray images. *Computers in Biology and Medicine*, 132:104319, 2021. 1

[17] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014. 1

[18] Janaki Sivakumar, K Thangavel, and P Saravanan. Computed radiography skull image enhancement using wiener filter. In *International Conference on Pattern Recognition, Informatics and Medical Engineering (PRIME-2012)*, pages 307–311. IEEE, 2012. 1

[19] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2818–2826, 2016. 1

[20] Tolga. Chest x-ray images. https://www.kaggle.com/datasets/tolgadincer/labeled-chest-xray-images, 2020. 1

[21] Olivier Vandenberg, Delphine Martiny, Olivier Rochas, Alex van Belkum, and Zisis Kozlakidis. Considerations for diagnostic covid-19 tests. *Nature Reviews Microbiology*, 19(3):171–183, 2021. 1

[22] Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, and Ronald M Summers. Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2097–2106, 2017. 1

[23] Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, and Ronald M Summers. Nih chest x-rays. https://www.kaggle.com/datasets/nih-chest-xrays/data, 2017. 1