Midterm Report

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October 15, 2023

1 Introduction

Deploying neural networks for the classification of medical images is a challenging task, due to the fact, that most clinical samples are by magnitudes smaller than usual datasets used to train multimillion parameter convolutional neural networks such as ResNet50 [He et al., 2016], VGG16 [Simonyan and Zisserman, 2014] or Unet [Ronneberger et al., 2015]. The task is further complicated that human anatomy is highly complex and variable and thus imposes a challenge to the generalization capabilities of models. Besides that medical imagery such as CT, MRI or X-Ray scans are often subject to very high nuisance due to patient movement and other technical artefacts. Pneumonia is the inflammation of the lung's alveoli and their subsequent filling with fluid potentially leading up to life threatening condition. Aim of this project is to compare multiple approaches to increase the predictive performance of pneumonia.

2 Background and related work

2.1 Pneumonia

Oxygen exchange in the lungs occurs in the alveoli, often referred to as air sacs, which are located at the termini of the bronchial tree. The movement of extracellular fluid between tissues and blood flow is governed by the Starling equation, which can roughly be expressed as:
Fluid flow $= [P_c - P_i] - [\pi_p - \pi_i] = \Delta P - \Delta\pi$. Thereby is P_c is the hydrostatic pressure in the capillary and P_i the hydrostatic pressure of the tissue. π_p is the osmotic pressure of the blood and π_i the osmotice pressure of the tissue. If the permeability of the membran increases due to inflammation, or the hydrostatic pressure increases drastically the alveoli start to fill up with fluid as can be seen in figure 1. As the oxygen exchange is impaired by the fluid concentration pneumonia poses a severe threat to a patient's life [Ware and Matthay, 2005].

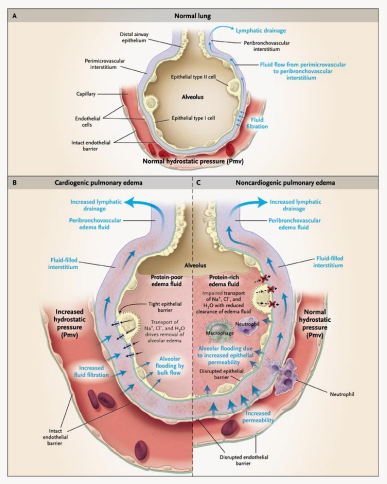
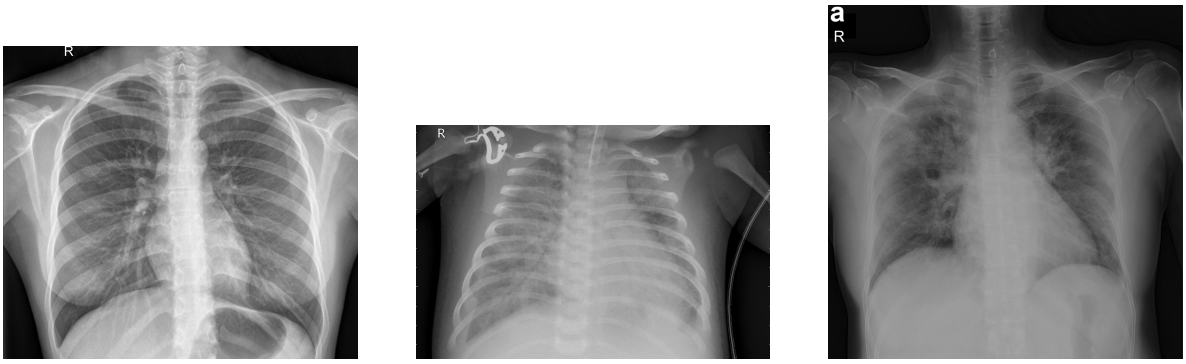


Figure 1: Alveoli of the lung and its relation to the starling equation as used by [Ware and Matthay, 2005].

As the density increases with the fluid concentration the alveoli start to turn white on an X-Ray image, which are thus the common method to diagnose pneumonia.



(a) A (b) B (c) C

Figure 2: A shows a chest XRay of a healthy patient. Both lungs are clearly visible as darker areas. B shows a chest XRay of a patient suffering from non-viral pneumonia and C the XRay Covid19 induced pneumonia. In both images the fluid infiltrated alveoli let the lung appear white to grayish where as the air filled bronchi appear as dark lines.

Pneumonia leads annualy to more than 2.5 million deaths of which almost 15% are less than 5 years old [Sharma and Guleria, 2023]. The biggest publicly available dataset of chest XRays is called CXR and contains more than 18,000 images [Nguyen et al., 2020], which contains around 3% pneumonia images.

2.2 Related work

[Sharma and Guleria, 2023] presents multiple approaches for the detection of pneumonia using chest XRays. The Approaches so far can be categorized into CNN-based models, the use of pre-trained models as well as ensemble models.

CNN-based models train the freshly intialized models and solely train them on XRay images; examples could be [Huang et al., 2021] or [Jakhar and Hooda, 2018].

Transfer learning is an approach, which tries to utilize information, that was already learned on a source domain on a so called target domain. In the context of medical imagery image classification networks, which already have been trained on the ImageNet [Deng et al., 2009] - a large dataset containing more than 14 million annotated images belonging to over 20,000 categories. These models are hence already capable of feature detection and image classification. In order to deploy them on a target domain the vast majority of parameters gets frozen - i.e. they are not updated during the learning process - and the head of the model is either replaced or augmented with a new layer [Zhuang et al., 2020]. In [El Asnaoui et al., 2021] compared numerous image classification networks and their respective transfer capabilites.

Ensemble models resemble to technique of using multiple related models and integrating their outputs to a result - a simple example for this would be a random forest model, where the output of multiple decision trees is aggregated to a single prediction. This technique is however not limited to the use of simple models: [Toğaçar et al., 2020] combined VGG16, AlexNet and VGG19 to extract features of chest XRay for classification.

3 Progress so far

This project aims to explore, analyze, and juxtapose the aforementioned methodologies for pneumonia identification, leveraging diverse paradigms to elucidate their respective efficacies and implications in the nuanced realm of medical image diagnostics.

For this task the dataset [Cohen et al., 2020] was chosen, which contains 6432 chest XRays and CT scans of 472 patients. Table 1 shows the distribution of diagnosis, which can be used as labels and

sex	count	age		Modalities present	count
M	270	mean	54.39	['X-ray']	427
F	158	std	17.21	['CT']	23
unknown	44			['X-ray' 'CT']	22

Table 2: Summary statistics of the present sample

table 2 shows the summary statistics of the patient cohort. The diagnosis can be aggregated to the three classes healthy, Pneumonia, Covid19.

Label	Count
Pneumonia/Viral/COVID-19	307
Pneumonia	39
Pneumonia/Fungal/Pneumocystis	17
No Finding	17
Tuberculosis	10
Pneumonia/Bacterial/Streptococcus	9
Pneumonia/Viral/SARS	8
Pneumonia/Bacterial/Legionella	6
Pneumonia/Lipoid	6
Pneumonia/Bacterial/Klebsiella	5
Pneumonia/Viral/MERS-CoV	4
Pneumonia/Bacterial/Mycoplasma	3
Pneumonia/Viral/Influenza	3
Pneumonia/Fungal/Aspergillosis	2
Pneumonia/Viral/Varicella	2
Pneumonia/Viral/Influenza/H1N1	1
Unknown	26
Pneumonia/Bacterial/E.Coli	1
Pneumonia/Viral/Herpes	1
Pneumonia/Bacterial	1
Pneumonia/Bacterial/Chlamydophila	1
Pneumonia/Bacterial/Staphylococcus/MRSA	1
Pneumonia/Bacterial/Nocardia	1
Pneumonia/Aspiration	1

Table 1: Present diagnosis in the sample

We have managed to get access to IU's HPC carbonate, downloaded and extracted the data and started to implement a dataloader for the images as well as to conduct first experiments using pre-trained models as ResNet50 and VGG16.

4 Revised research plan

- Week 1: October 12 - October 18, 2023 In this week we will be thoroughly analysing the image data and trying to work our way towards finding the prominent features in the dataset. Mayur and Leo will be working on this.
- Week 2: October 19 - October 25, 2023 In this week we have to get started by studying the documentation on models like ResNet50 or OCR and how it can be used for image detection. Mayur and Kaushik will be working on the documentation.
- Week 3: October 26 - November 1, 2023 During this week we look for some old cases, where

ResNet50 and VGG16 has been utilised in medical analytics and run them if possible. Leo and Kaushik will work on this.

- Week 4: November 2 - November 8, 2023 This week is where we try to analyse the working of different models on our dataset. All three will work on this together by separating the different aspects of the problem.
- Week 5: November 9 - November 15, 2023 In this week we will try to work on validation sets and try to get training, testing and validation set accuracy. We will try K fold cross validation or some other methods to find the best way. All three will be working together on this.
- Week 6: November 16 - November 22, 2023 Once we see our model working fine, we will try to generate visuals for the outcomes and intermediate steps. Leo and Mayur will work on this.
- Week 7: November 23 - November 29, 2023 One buffer week to work on fine tuning the hyper parameters and getting better results or solving any issues. All three will have to work on this.
- Week 8: November 30 - December 6, 2023 We start with the final documentation of our project. Kaushik will handle this, while Mayur and Leo take over the presentation work.
- December 7, 2023

We conclude the project along with the code and documentation.

References

[Cohen et al., 2020] Cohen, J. P., Morrison, P., and Dao, L. (2020). Covid-19 image data collection. *arXiv 2003.11597*.

[Deng et al., 2009] Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. (2009). Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee.

[El Asnaoui et al., 2021] El Asnaoui, K., Chawki, Y., and Idri, A. (2021). Automated methods for detection and classification pneumonia based on x-ray images using deep learning. In *Artificial intelligence and blockchain for future cybersecurity applications*, pages 257–284. Springer.

[He et al., 2016] He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778.

[Huang et al., 2021] Huang, Z., Liu, X., Wang, R., Zhang, M., Zeng, X., Liu, J., Yang, Y., Liu, X., Zheng, H., Liang, D., et al. (2021). Fanet: fast assessment network for the novel coronavirus (covid-19) pneumonia based on 3d ct imaging and clinical symptoms. *Applied Intelligence*, 51:2838–2849.

[Jakhar and Hooda, 2018] Jakhar, K. and Hooda, N. (2018). Big data deep learning framework using keras: A case study of pneumonia prediction. In *2018 4th International Conference on computing communication and automation (ICCCA)*, pages 1–5. IEEE.

[Nguyen et al., 2020] Nguyen, H. Q., Lam, K., Le, L. T., Pham, H. H., Tran, D. Q., Nguyen, D. B., Le, D. D., Pham, C. M., Tong, H. T. T., Dinh, D. H., Do, C. D., Doan, L. T., Nguyen, C. N., Nguyen, B. T., Nguyen, Q. V., Hoang, A. D., Phan, H. N., Nguyen, A. T., Ho, P. H., Ngo, D. T., Nguyen, N. T., Nguyen, N. T., Dao, M., and Vu, V. (2020). Vindr-cxr: An open dataset of chest x-rays with radiologist's annotations.

[Ronneberger et al., 2015] Ronneberger, O., Fischer, P., and Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*, pages 234–241. Springer.

[Sharma and Guleria, 2023] Sharma, S. and Guleria, K. (2023). A systematic literature review on deep learning approaches for pneumonia detection using chest x-ray images. *Multimedia Tools and Applications*, pages 1–51.

[Simonyan and Zisserman, 2014] Simonyan, K. and Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

[Toğaçar et al., 2020] Toğaçar, M., Ergen, B., Cömert, Z., and Özyurt, F. (2020). A deep feature learning model for pneumonia detection applying a combination of mrmr feature selection and machine learning models. *Irbm*, 41(4):212–222.

[Ware and Matthay, 2005] Ware, L. B. and Matthay, M. A. (2005). Acute pulmonary edema. *New England Journal of Medicine*, 353(26):2788–2796.

[Zhuang et al., 2020] Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., and He, Q. (2020). A comprehensive survey on transfer learning. *Proceedings of the IEEE*, 109(1):43–76.