

CLASSIFICATION OF LUNG DISEASES FROM X-RAY IMAGES
USING DEEP LEARNING

TAN ZHENG YU

A project report submitted in fulfilment of the
requirements for the award of the degree of
Master of Engineering (Computer and Microelectronic Systems)

School of Electrical Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

FEBRUARY 2022

DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

ACKNOWLEDGEMENT

First, I would like to convey my deepest thanks and appreciation to supervisor for this project, Associate Professor Dr Eileen Su Lee Ming, for all her supervision and encouragement given throughout the completion of this project. She helped me to solve the problems that I faced while completing the project and provided several opportunities for me to explore new knowledge and to make decisions. Without her useful guidance and countless support, it is impossible for me to complete this report successfully.

Next, I would like to take this opportunity to thank all my lecturers who have taught and guided me throughout the years of studying life in UTM. They were willing to help and guide their students in every project and subject. Without the guidance and knowledge given, I believe that I would not be able to complete this final year project.

Not forgetting my deepest gratitude to my beloved family, especially my parents for their encouragement, constructive suggestions, and motivational support throughout the project completion, from the beginning till the end.

Last but not least, thanks to all my friends and course mates who have supported and helped me directly and indirectly throughout the completion of this report. Their help, ideas, advice, and moral support really helped me in getting through the hardships while completing this project.

ABSTRACT

The lung disease, due to COVID-19 for example, has caused devastation around the world. Even in the most developed nations, the growing number of cases has overwhelmed healthcare facilities. Radiographic imaging is still the most convenient screening method for lung diseases. A certified radiologist interprets the chest X-ray image according to their experience level. As such, the interpretations might vary for different radiologists based on the observed characteristics and due to possibility of human error. To counter this problem, an automated lung disease classification system using chest X-ray was proposed. The classification was achieved by using deep learning approach because artificial intelligence has been proven to help reduce human error in medical applications. In this project, five deep learning architectures namely ResNet18, ResNet50, ResNet101, Alexnet, and VGG16 architectures were selected for transfer learning and classification of lung diseases. The lung X-ray images were classified into five output classes, namely COVID-19, pneumonia, tuberculosis, nodule or normal lungs. Images from multiple public datasets were acquired to be used as train set and test set for this automated lung disease classification model. The five deep learning models were successfully tested, and the highest accuracy was 96.3%, achieved with the Alexnet architecture.

ABSTRAK

Penyakit paru-paru, seperti yang diakibatkan oleh COVID-19, telah menyebabkan kehancuran di seluruh dunia. Bahkan di negara-negara yang paling maju, jumlah kes yang semakin banyak telah membanjiri kemudahan penjagaan kesihatan. Pengimejan radiografi merupakan kaedah pemeriksaan yang paling sesuai untuk penyakit paru-paru. Ahli radiologi yang diperakui menafsirkan gambar sinar-X dada mengikut tahap pengalaman mereka. Oleh itu, penafsiran mungkin berbeza untuk ahli radiologi yang berbeza berdasarkan ciri-ciri yang diperhatikan dan disebabkan kemungkinan kesalahan manusia. Untuk mengatasi masalah ini, sistem klasifikasi penyakit paru-paru automatik dari sinar-X dada dicadangkan. Klasifikasi tersebut dicapai dengan menggunakan pendekatan pembelajaran mendalam kerana kecerdasan buatan telah terbukti dapat membantu mengurangkan kesilapan manusia dalam aplikasi perubatan. Senibina ResNet18, ResNet50 ResNet101, Alexnet, dan VGG16 dipilih untuk pembelajaran transfer dalam projek ini untuk mengklasifikasikan penyakit paru-paru menjadi lima kelas, iaitu COVID-19, pneumonia, tuberculosis, nodul, dan paru-paru normal. Beberapa set data awam digabungkan dan digunakan sebagai set Latihan dan set ujian untuk model klasifikasi penyakit paru-paru automatic ini. Lima model pembelajaran mendalam Berjaya diuji dan ketepatan tertinggi adalah 96.3%, dicapai dengan seni bina AlexNet.

TABLE OF CONTENTS

	TITLE	PAGE
	DECLARATION	vi
	DEDICATION	vii
	ACKNOWLEDGEMENT	viii
	ABSTRACT	ix
	ABSTRAK	x
	TABLE OF CONTENTS	xi
	LIST OF TABLES	xiv
	LIST OF FIGURES	xv
	LIST OF ABBREVIATIONS	xvi
	LIST OF APPENDICES	xvii
CHAPTER 1	INTRODUCTION	1
1.1	Background	1
1.2	Problem Statement	3
1.3	Research Objectives	4
1.4	Scope of Work	4
1.5	Report Organization	5
CHAPTER 2	LITERATURE REVIEW	7
2.1	Introduction	7
2.2	Lung Diseases Classification System	7
2.2.1	Type of Lung Diseases	8
2.2.1.1	Tuberculosis	8
2.2.1.2	Pneumonia	8
2.2.1.3	COVID-19	8
2.2.1.4	Nodule	9
2.2.2	Image Type	9
2.2.2.1	Chest X-rays (CXR)	9

2.2.2.2	CT Scans	10
2.2.2.3	PET scan	11
2.2.3	Public Dataset	12
2.2.4	Deep Learning Technique	13
2.3	Previous Research Work	17
2.4	Chapter Summary	23
CHAPTER 3	RESEARCH METHODOLOGY	24
3.1	Introduction	24
3.2	Development Tool	26
3.3	Image acquisition	26
3.4	Network Training	28
3.4.1	Transfer Learning	28
3.4.2	Data Augmentation	30
3.4.3	Early Stopping Function	31
3.5	Network Testing	32
3.5.1	Stratified K-fold Cross-validation	32
3.5.2	Performance metrics	33
3.6	Architectures	35
3.6.1	VGG16	35
3.6.2	AlexNet	36
3.6.3	ResNet	37
3.7	Chapter Summary	39
CHAPTER 4	RESULTS & DISCUSSION	41
4.1	Introduction	41
4.2	Input Image Preprocessing	41
4.3	Training Process	42
4.4	Testing Process	43
4.4.1	Network performance	43
4.4.2	Confusion Matrix and evaluation parameters	47
4.5	Discussion	53
4.6	Chapter Summary	54

CHAPTER 5	CONCLUSION AND RECOMMENDATIONS	55
5.1	Conclusion	55
5.2	Contributions	55
5.3	Recommendation of Future Work	56
REFERENCES		57
APPENDIX		67

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 2.1	CXR datasets for each disease	13
Table 2.2	Summary of previous related work	20
Table 3.1	Hardware specifications	26
Table 3.2	Selected dataset for training and testing	27
Table 3.3	Type of augmentation applied	31
Table 3.4	Confusion matrix	34
Table 3.5	Architectures for Resnet18, Resnet50, and Resnet101	38
Table 3.6	Transfer learning	39
Table 4.1	5-fold validation accuracy for AlexNet, ResNet18, ResNet50, ResNet101, and VGG16	44
Table 4.2	5-fold testing accuracy for AlexNet, ResNet18, ResNet50, ResNet101, and VGG16	45
Table 4.3	5-fold training loss for AlexNet, ResNet18, ResNet50, ResNet101, and VGG16	45
Table 4.4	5-fold training duration for AlexNet, ResNet18, ResNet50, ResNet101, and VGG16 (minutes)	46
Table 4.5	time taken for classification per image (seconds)	46
Table 4.6	5-fold training epochs for AlexNet, ResNet18, ResNet50, ResNet101, and VGG16	46
Table 4.7	Recall, precision, F1-score, and accuracy for AlexNet	49
Table 4.8	Recall, precision, F1-score, and accuracy for ResNet18	50
Table 4.9	Recall, precision, F1-score, and accuracy for ResNet50	51
Table 4.10	Recall, precision, F1-score, and accuracy for ResNet101	52
Table 4.11	Recall, precision, F1-score, and accuracy for VGG16	53

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2.1	CXR image	10
Figure 2.2	CT scan image	11
Figure 2.3	PET scan image	12
Figure 2.4	Performance of deep learning versus older learning algorithms	14
Figure 2.5	Architecture of a traditional CNN	15
Figure 2.6	(a) Neural network before dropout (b) Neural network after dropout	16
Figure 3.1	Process flow chart	25
Figure 3.2	Usage of training Set, validation set, and test set	28
Figure 3.3	Implementation of transfer learning	30
Figure 3.4	Early stopping function	32
Figure 3.5	Stratified 5-fold cross-validation	33
Figure 3.6	Architecture for VGG16	36
Figure 3.7	Architecture for AlexNet	37
Figure 3.8	ResNet Architecture	38
Figure 4.1	Sample image before and after augmentation	42
Figure 4.2	Training progress	42
Figure 4.3	Confusion matrix for Alexnet	48
Figure 4.4	Confusion matrix for Resnet18	49
Figure 4.5	Confusion matrix for Resnet50	50
Figure 4.6	Confusion matrix for Resnet101	51
Figure 4.7	Confusion matrix for VGG16	52

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
AI	-	artificial intelligent
CAP	-	community-acquired pneumonia
CNN	-	Convolutional Neural network
COVID-19	-	Coronavirus disease
CT	-	Computerized tomography
CXR	-	Chest X-ray
FeNO	-	Fractional exhaled nitric oxide
FN	-	False Negative
FP	-	False Positive
Grad-CAM	-	Gradient Class Activation Map
GUI	-	graphical user interface
HU	-	Hounsfield Units
JSRT	-	Japanese Society of Radiological Technology
MATLAB	-	Matrix Laboratory
MRI	-	magnetic resonance imaging
NIH	-	National Institutes of Health
PCA	-	principal component analysis
PET	-	positron emission tomography
RT-PCR	-	reverse transcription-polymerase chain reaction
STN	-	spatial transformer network
TB	-	Tuberculosis
TN	-	True Negative
TP	-	True Positive
UTM	-	Universiti Teknologi Malaysia
WHO	-	World Health Organization
YOLO	-	You Only Look Once

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	MATLAB code	67

CHAPTER 1

INTRODUCTION

1.1 Background

Lung disease is defined as any condition in the lungs that prevents the lungs from performing correctly[1]. Lung disease is one of the main causes of death in Malaysia [2]. Lung diseases can be categorised into 3 main types, such as lung tissue disease, airway disease, and lung circulation disease. Each of the disease category affects the lungs in a different way. Most of the common lung diseases fall into more than one category at once according to their impact [3]. Airway disease refers to diseases like asthma; affecting the airways that carry gases into and out of lungs [4]. Any scarring or inflammation of the lung tissue is categorised as lung tissue diseases [5]. The example of lung tissue diseases includes sarcoidosis, Sjogren's syndrome, scleroderma, and others. Lung circulation disease is caused by the damage of vessels in lungs and reduction in oxygen absorption [6]. The most common example for lung circulation disease is pulmonary hypertension. Most of the lung diseases shared common symptoms like cough, wheezing, shortness of breath, chest illness and others [7]. Doctors will determine the proper diagnostic tests to assess an individual based on the patient's symptoms.

The available diagnostic tests for lung diseases can be divided into four categories, which are simple tests, advanced tests, invasive tests, and imaging test [8]. Both simple tests and advanced tests basically help to measure how much volume of air the patient's lungs can hold by requiring the patient to blow air into a tube. The advanced test will provide more accurate results compared to simple tests by including additional steps during the test. The example of simple tests include spirometry [9] and FeNO test [10] while the example of advanced tests include plethysmography [11] and diffusion capacity test [12]. Invasive test refers to the test where the trained operator inserts a medical instrument into patient's body via cut skin or natural orifice [13].

Invasive test usually provides results with higher sensitivity and precision compared to other tests but it required expertise in handling the test and is time-consuming [14]. The example of imaging tests includes chest X-Ray (CXR), computerized tomography (CT), magnetic resonance imaging (MRI), position emission tomography (PET) scans and others. CXR imaging is the most common and preferred diagnostic examination in clinical care as it is painless, fast, relatively economical, and non-invasive. The radiography image is mainly used for detection, staging, follow-up, and quantification of lung disease [15].

In Malaysia, most of the lung illnesses are discovered when the diseases have progressed to the late stages [16]. The development of tools and systems that allow for faster and more precise diagnosis is critical in the world today. Image based lung diseases classification system play an important role in this and are now being expanded. Most of the existing research has focused on lung diseases classification based on textural characteristics and it demonstrated its effectiveness in classification potential [17]. Deep features, on the other hand, have emerged as a more promising path ahead in recent research. This is because it demonstrates a new level of robustness and wide depth of features that were previously unavailable. However, the training time and computational load of using huge feature sets is a key disadvantage of such approaches. Besides that, the performance of classification system is highly dependent on the training result from extracted features. Deep learning approach has recently gain popularity in the real-world application due to its ability to perform feature extraction and classification automatically [18].

Deep learning concept appeared firstly during 2006 as a new field of research within machine learning [19]. It has been widely implemented in many research fields related to pattern recognition. Deep learning model uses a cascade of multilayer of nonlinear processing units to perform feature extraction and classification. The learning process of deep learning could be supervised or unsupervised. Supervised learning refers to learning process with labelled target classes while unsupervised learning refers to learning process without labelled target classes [20]. One of the advantages of deep learning is its ability to perform automatic feature extraction instead of classifying handpicked feature based on domain-specific knowledge. This

helps in detecting and classifying certain medical conditions effectively [21]. Many deep learning algorithms are trained to solve specific tasks, and if the feature changes, the models must be rebuilt from scratch. Transfer learning overcomes such drawback by utilizing knowledge acquired for old task to solve another new task. Transfer learning gives better performance result with smaller sample size data due to its pre-trained weights and improved efficiency. The pre-trained model is a model that was trained on a large benchmark dataset like ImageNet to solve a general problem [22]. The example for pre-trained model includes VGG16, ResNet, AlexNet, EfficientNet, GoogleNet, and others.

1.2 Problem Statement

CXR image-based lung disease detection is highly dependent on the diagnosis of the radiologists. According to Ang et al [23], there are 38.8% of misdiagnosis in community-acquired pneumonia (CAP) in Penang General Hospital while Poh et al. [24] reported 64.5% of inaccurate diagnosis of pneumonia by the emergency department of Hospital Tuanku Ja'afar Seremban. Most of the misdiagnosis was due to human error during the diagnosis of CXR images.

Most lung disease classification research only focused on one to two types of diseases. Some of the lung diseases shared similar characteristics that may confuse the algorithm. Hence, existing lung classification system may have lower performance when extended to classifying varieties of diseases due to the increased difficulty.

Besides, there are existing research that claimed to have higher accuracy by using smaller datasets. Smaller dataset could mean that some images had been excluded, particularly if those images did not provide good results. Hence, the lung disease classification system may not be able to achieve the same level of accuracy when dealing with larger and noisy datasets, thus making it impractical to be implemented for actual medical applications.

1.3 Research Objectives

- (a) To implement a lung disease classification system on MATLAB platform using lung X-ray images and transfer learning method in deep learning neural network
- (b) To classify the lung X-ray images into five target classes of lung conditions (normal, pneumonia, tuberculosis, COVID-19, and nodule) with more than 90% accuracy
- (c) To evaluate the performance of deep learning networks for classification of lung diseases

1.4 Scope of Work

- (a) The lung diseases classification system utilized the lung samples from multiple selected public datasets.
- (b) The neural network was trained using X-ray images of healthy lung and diseased lungs, with nodule, tuberculosis, pneumonia and COVID-19.
- (c) AlexNet, ResNet18, ResNet50, ResNet101, and VGG16 were selected as pre-trained networks to be used in transfer learning process.
- (d) The lung samples obtained from public datasets have only one single type of disease per image.

1.5 Report Organization

The purpose of this report is to develop a lung disease classification system using a transfer learning approach and to assess the system using a variety of deep learning networks. The overall five chapters in the report are organized in the following sequences: introduction, literature review, research methodology, preliminary results, as well as the conclusion and recommendation.

The first chapter introduces and give brief information about the purpose of the study. The introduction concludes the overview of the entire topic of study. The problem statements, research objectives and the related scopes on each objective are all included in this chapter.

Chapter 2 provides a literature review of the research on lung diseases classification system. This chapter gives a general review on the background of lung diseases, image type, public dataset, and deep learning technique. Then, the trends in developing deep learning-based lung diseases classification system are included. Lastly, research on lung diseases classification system is discussed focusing on the outcome measure used by each system.

Chapter 3 is focusing on the research methodology. All research activities in image acquisition, network training, network testing was presented in detail. These include the pre-processing and the experiments conducted to implement the system. The flow of developing the lung diseases classification system is described and presented in graphical form. This includes the performance metrics.

Chapter 4 presents the results and discussion. The overall experimental and simulation results such as input image pre-processing, training process, and testing

process are presented and analysed in this chapter. The result from the experiment are presented in graphical form like table and chart for easier analysis.

Chapter 5 is the summary and conclusion of the entire research paper. It summarises the essential elements of the main study topic as well as concluding the final obtained result to justify the result is acceptable or not. Any recommendations for further research as well as the limitations encountered during the study are explored.

REFERENCES

- [1] M. Kraft, "Approach to the Patient with Respiratory Disease," in *Goldman's Cecil Medicine: Twenty sixth Edition*, 26th ed., vol. 1, Elsevier, 2020, pp. 512–516.
- [2] Dato' Sri Dr. Mohd Uzir Mahidin, "Statistics on Causes of Death, Malaysia, 2020," KUALA LUMPUR, 2020. [Online]. Available: https://www.dosm.gov.my/v1/index.php?r=column/cthemByCat&cat=401&bul_id=QTU5T0dKQ1g4MHYxd3ZpMzhEMzdRdz09&menu_id=L0pheU43NWJwRWVSZklWdzQ4TlhUUT09.
- [3] A. Barrell, "Lung diseases: What to know," *Medical News Today*, Apr. 28, 2021.
- [4] D. P. Potaczek, S. Miethe, V. Schindler, F. Alhamdan, and H. Garn, "Role of airway epithelial cells in the development of different asthma phenotypes," *Cell. Signal.*, vol. 69, no. January, p. 109523, 2020, doi: 10.1016/j.cellsig.2019.109523.
- [5] R. P. Oliveira, R. Ribeiro, L. Melo, B. Grima, S. Oliveira, and J. D. Alves, "Connective tissue disease-associated interstitial lung disease," *Pulmonology*, pp. 224–232, 2020, doi: 10.1016/j.pulmoe.2020.01.004.
- [6] S. Yaghi, A. Novikov, and T. Trandafirescu, "Clinical update on pulmonary hypertension," *J. Investig. Med.*, vol. 68, no. 4, pp. 821–827, 2020, doi: 10.1136/jim-2020-001291.
- [7] K. R. *et al.*, "Respiratory symptoms in young adults and future lung disease the cardia lung study," *Am. J. Respir. Crit. Care Med.*, vol. 197, no. 12, pp. 1616–1624, 2018, [Online]. Available: <http://www.embase.com/search/results?subaction=viewrecord&from=export&id=L622728015%0Ahttp://dx.doi.org/10.1164/rccm.201710-2108OC>.
- [8] S. Felson, "Common Lung Diagnostic Tests," *WebMD*, Sep. 13, 2020.
- [9] E. V. Mancuzo *et al.*, "Spirometry results after treatment for pulmonary tuberculosis: Comparison between patients with and without previous lung disease: A multicenter study," *J. Bras. Pneumol.*, vol. 46, no. 2, pp. 1–9, 2020, doi: 10.36416/1806-3756/e20180198.

- [10] N. Bougard *et al.*, “Assessment of diagnostic accuracy of lung function indices and FeNO for a positive methacholine challenge,” *Biochem. Pharmacol.*, vol. 179, no. April, p. 113981, 2020, doi: 10.1016/j.bcp.2020.113981.
- [11] E. Eber, Ed., “ERS Handbook of Paediatric Respiratory Medicine,” in *ERS Handbook of Paediatric Respiratory Medicine*, 2021, pp. 80–88.
- [12] A. M. Preisser, K. Schlemmer, R. Herold, A. Laqmani, C. Terschüren, and V. Harth, “Relations between vital capacity, CO diffusion capacity and computed tomographic findings of former asbestos-exposed patients: A cross-sectional study,” *J. Occup. Med. Toxicol.*, vol. 15, no. 1, pp. 1–11, 2020, doi: 10.1186/s12995-020-00272-1.
- [13] S. Cousins, N. S. Blencowe, and J. M. Blazeby, “What is an invasive procedure? A definition to inform study design, evidence synthesis and research tracking,” *BMJ Open*, vol. 9, no. 7, 2019, doi: 10.1136/bmjopen-2018-028576.
- [14] T. Glaab, C. Taube, A. Braun, and W. Mitzner, “Invasive and noninvasive methods for studying pulmonary function in mice,” *Respir. Res.*, vol. 8, 2007, doi: 10.1186/1465-9921-8-63.
- [15] M. Wielpütz, C. P. Heußel, F. F. Herth, and H. Kauczor, “Radiological Diagnosis in Lung Disease,” *Dtsch. Arztebl. Int.*, vol. 111, no. 11, pp. 181–187, 2014.
- [16] “Malaysia: Lung Disease. In World Health Rankings,” 2012. <http://www.worldlifeexpectancy.com/malaysia-lung-disease>.
- [17] P. Cirujeda *et al.*, “A 3-D Riesz-Covariance Texture Model for Prediction of Nodule Recurrence in Lung CT,” *IEEE Trans. Med. Imaging*, vol. 35, no. 12, pp. 2620–2630, 2016, doi: 10.1109/TMI.2016.2591921.
- [18] F. Shaheen, B. Verma, and M. Asafuddoula, “Impact of Automatic Feature Extraction in Deep Learning Architecture,” *2016 Int. Conf. Digit. Image Comput. Tech. Appl. DICTA 2016*, 2016, doi: 10.1109/DICTA.2016.7797053.
- [19] V. M. Kota, V. Manoj Kumar, and C. Bharatiraja, “Deep Learning - A Review,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 912, no. 3, 2020, doi: 10.1088/1757-899X/912/3/032068.
- [20] R. Sathya and A. Abraham, “Comparison of Supervised and Unsupervised Learning Algorithms for Pattern Classification,” *Int. J. Adv. Res. Artif. Intell.*, vol. 2, no. 2, pp. 34–38, 2013, doi: 10.14569/ijarai.2013.020206.

- [21] S. T. Hwa Kieu, A. Bade, M. H. Ahmad Hijazi, and H. Kolivand, "A survey of deep learning for lung disease detection on medical images: State-of-the-art, taxonomy, issues and future directions," *J. Imaging*, vol. 6, no. 12, 2020, doi: 10.3390/jimaging6120131.
- [22] M. C. Phillips, R. Stein, and T. Park, "Analyzing Pre-Trained Neural Network Behavior with Layer Activation Optimization," *2020 Syst. Inf. Eng. Des. Symp. SIEDS 2020*, 2020, doi: 10.1109/SIEDS49339.2020.9106628.
- [23] A. C. Seong *et al.*, "Misdiagnosis of community-acquired pneumonia in patients admitted to respiratory wards, Penang general hospital," *Med. J. Malaysia*, vol. 75, no. 4, pp. 385–390, 2020.
- [24] P. K. Wei, "Diagnostic accuracy of pneumonia in Hospital Tuanku Ja'afar Seremban, a tertiary hospital," 2020.
- [25] M. A. S. Ali *et al.*, "A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis," *Lancet Digit. Heal.*, vol. 1, no. 6, pp. 1–13, 2019.
- [26] World Health Organisation, "Global Health TB Report," *World Heal. Organ. Geneva*, pp. 1–277, 2018, [Online]. Available: https://www.who.int/tb/publications/global_report/en/.
- [27] A. Yahiaoui, O. Er, and N. Yumusak, "A new method of automatic recognition for tuberculosis disease diagnosis using support vector machines," *Biomed. Res.*, vol. 28, no. 9, pp. 4208–4212, 2017.
- [28] S. Kumar, P. Singh, and M. Ranjan, "A review on deep learning based pneumonia detection systems," *Proc. - Int. Conf. Artif. Intell. Smart Syst. ICAIS 2021*, pp. 289–296, 2021, doi: 10.1109/ICAIS50930.2021.9395868.
- [29] W. H. Organisation, "Pneumonia," 2019. <https://www.who.int/news-room/fact-sheets/detail/pneumonia>.
- [30] World Health Organisation, "WHO Coronavirus (COVID-19) Dashboard," 2021. <https://covid19.who.int/> (accessed Jun. 27, 2021).
- [31] S. Sakib *et al.*, "Detection of COVID-19 Disease from Chest X-Ray Images: A Deep Transfer Learning Framework," *medRxiv*, no. June, pp. 8–13, 2020.
- [32] A. R. Larici *et al.*, "Lung nodules: Size still matters," *Eur. Respir. Rev.*, vol. 26, no. 146, 2017, doi: 10.1183/16000617.0025-2017.
- [33] D. E. Midthun, "Early detection of lung cancer," *F1000Research*, vol. 5, 2016, doi: 10.12688/f1000research.7313.1.

- [34] R. Ballabriga *et al.*, “Photon Counting Detectors for X-ray Imaging with Emphasis on CT,” vol. 7311, no. c, 2020, doi: 10.1109/TRPMS.2020.3002949.
- [35] P. Gang, W. Zhen, and W. Zeng, “Dimensionality Reduction in Deep Learning for Chest X-Ray Analysis of Lung Cancer,” no. c, pp. 878–883, 2018.
- [36] W. Ausawalaithong, “Automatic Lung Cancer Prediction from Chest X-ray Images Using the Deep Learning Approach,” 2018.
- [37] I. Sirazitdinov, M. Kholiavchenko, T. Mustafaev, Y. Yixuan, R. Kuleev, and B. Ibragimov, “Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database,” *Comput. Electr. Eng.*, vol. 78, pp. 388–399, 2019, doi: 10.1016/j.compeleceng.2019.08.004.
- [38] G. Liang and L. Zheng, “A transfer learning method with deep residual network for pediatric pneumonia diagnosis,” *Comput. Methods Programs Biomed.*, vol. 187, 2020, doi: 10.1016/j.cmpb.2019.06.023.
- [39] D. Varshni and L. Agarwal, “Pneumonia Detection Using CNN based Feature Extraction,” 2019.
- [40] E. Ayan and H. M. Ünver, “Diagnosis of pneumonia from chest X-ray images using deep learning,” *2019 Sci. Meet. Electr. Biomed. Eng. Comput. Sci. EBBT 2019*, pp. 7–11, 2019, doi: 10.1109/EBBT.2019.8741582.
- [41] R. Angeline and R. Vani, “ResNet:A convolutional Neural Network for detecting and diagnosing of coronavirus pneumonia,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1084, no. 1, p. 012011, 2021, doi: 10.1088/1757-899x/1084/1/012011.
- [42] Y. Chaudhary, M. Mehta, R. Sharma, D. Gupta, A. Khanna, and J. J. P. C. Rodrigues, “Efficient-CovidNet : Deep Learning Based COVID-19 Detection From Chest X-Ray Images,” 2021.
- [43] S. Basu, “Deep Learning for Screening COVID-19 using Chest X-Ray Images,” pp. 2521–2527, 2020.
- [44] S. H. Yoo, H. Geng, T. L. Chiu, S. K. Yu, D. C. Cho, and J. Heo, “Deep Learning-Based Decision-Tree Classifier for COVID-19 Diagnosis From Chest X-ray Imaging,” vol. 7, no. July, pp. 1–8, 2020, doi: 10.3389/fmed.2020.00427.
- [45] S. Rajpal, N. Lakhyani, A. K. Singh, R. Kohli, and N. Kumar, “Using handpicked features in conjunction with ResNet-50 for improved detection of

- COVID-19 from chest X-ray images,” *Chaos, Solitons and Fractals*, vol. 145, p. 110749, 2021, doi: 10.1016/j.chaos.2021.110749.
- [46] K. K. Singh and A. Singh, “Diagnosis of COVID-19 from chest X-ray images using wavelets-based depthwise convolution network,” *Big Data Min. Anal.*, vol. 4, no. 2, pp. 84–93, 2021, doi: 10.26599/BDMA.2020.9020012.
- [47] B. K. Umri, M. Wafa Akhyari, and K. Kusriani, “Detection of COVID-19 in Chest X-ray Image using CLAHE and Convolutional Neural Network,” *2020 2nd Int. Conf. Cybern. Intell. Syst. ICORIS 2020*, 2020, doi: 10.1109/ICORIS50180.2020.9320806.
- [48] Z. Karhan and F. Akal, “Covid-19 Classification Using Deep Learning in Chest X-Ray Images,” *TIPTEKNO 2020 - Tip Teknol. Kongresi - 2020 Med. Technol. Congr. TIPTEKNO 2020*, 2020, doi: 10.1109/TIPTEKNO50054.2020.9299315.
- [49] X. Li, “A Solitary Feature-Based Lung Nodule Detection Approach for Chest X-Ray Radiographs,” vol. 22, no. 2, pp. 516–524, 2018.
- [50] S. Stirenko, Y. Kochura, and O. Alienin, “Chest X-Ray Analysis of Tuberculosis by Deep Learning with Segmentation and Augmentation,” pp. 422–428, 2018.
- [51] U. K. Lopes and J. F. Valiati, “Pre-trained convolutional neural networks as feature extractors for tuberculosis detection,” *Comput. Biol. Med.*, vol. 89, no. August, pp. 135–143, 2017, doi: 10.1016/j.compbimed.2017.08.001.
- [52] P. Whiting, “Computed tomography of the chest: I. Basic principles,” *BJA Educ.*, vol. 15, no. 6, pp. 299–304, 2015, [Online]. Available: <https://doi.org/10.1093/bjaceaccp/mku063>.
- [53] L. Talalwa, G. Natour, A. Bauer, A. Drzezga, and S. Beer, “Radiological characteristics of a new experimental rubber elastomeric polymer used in three-dimensional printing with different infill densities and patterns Radiological characteristics of a new experimental rubber elastomeric polymer used in three-dimen,” 2020.
- [54] S. Patil and A. Golellu, “Classification of COVID-19 CT images using transfer learning models,” *2021 Int. Conf. Emerg. Smart Comput. Informatics, ESCI 2021*, pp. 116–119, 2021, doi: 10.1109/ESCI50559.2021.9396773.
- [55] N. Ewen and N. Khan, “TARGETED SELF SUPERVISION FOR CLASSIFICATION ON A SMALL COVID-19 CT Data Science , Ryerson

- University , Toronto , ON Electrical , Computer , and Biomedical Engineering , Ryerson University , Toronto , ON,” pp. 1481–1485, 2021.
- [56] M. R. Islam and A. Matin, “Detection of COVID 19 from CT Image by the Novel LeNet-5 CNN Architecture,” *ICCIT 2020 - 23rd Int. Conf. Comput. Inf. Technol. Proc.*, pp. 19–21, 2020, doi: 10.1109/ICCIT51783.2020.9392723.
- [57] M. Vas and A. Dessai, “Lung cancer detection system using lung CT image processing,” *2017 Int. Conf. Comput. Commun. Control Autom. ICCUBEA 2017*, 2018, doi: 10.1109/ICCUBEA.2017.8463851.
- [58] N. S. Nadkarni and S. Borkar, “Detection of lung cancer in CT images using image processing,” *Proc. Int. Conf. Trends Electron. Informatics, ICOEI 2019*, vol. 2019-April, no. Icoei, pp. 863–866, 2019, doi: 10.1109/icoei.2019.8862577.
- [59] A. Hoque, A. K. M. A. Farabi, F. Ahmed, and M. Z. Islam, “Automated Detection of Lung Cancer Using CT Scan Images,” *2020 IEEE Reg. 10 Symp. TENSYP 2020*, no. June, pp. 1030–1033, 2020, doi: 10.1109/TENSYP50017.2020.9230861.
- [60] G. Ling and C. Cao, “Automatic Detection and Diagnosis of Severe Viral Pneumonia CT Images Based on LDA-SVM,” *IEEE Sens. J.*, vol. 20, no. 20, pp. 11927–11934, 2020, doi: 10.1109/JSEN.2019.2959617.
- [61] X. Qian *et al.*, “M3Lung-Sys: A Deep Learning System for Multi-Class Lung Pneumonia Screening from CT Imaging,” *IEEE J. Biomed. Heal. Informatics*, vol. 24, no. 12, pp. 3539–3550, 2020, doi: 10.1109/JBHI.2020.3030853.
- [62] Q. Wang, D. Yang, Z. Li, X. Zhang, and C. Liu, “Deep regression via multi-channel multi-modal learning for pneumonia screening,” *IEEE Access*, vol. 8, pp. 78530–78541, 2020, doi: 10.1109/ACCESS.2020.2990423.
- [63] A. Yang, X. Jin, and L. Li, “CT images recognition of pulmonary tuberculosis based on improved faster RCNN and U-net,” *Proc. - 10th Int. Conf. Inf. Technol. Med. Educ. ITME 2019*, pp. 93–97, 2019, doi: 10.1109/ITME.2019.00032.
- [64] M. Shawky, Z. A. E. Ali, D. H. Hashem, and M. Houseni, “Role of positron-emission tomography/computed tomography (PET/CT) in breast cancer,” *Egypt. J. Radiol. Nucl. Med.*, vol. 51, no. 1, 2020, doi: 10.1186/s43055-020-00244-9.

- [65] A. Kumar, M. Fulham, D. Feng, and J. Kim, “Co-Learning Feature Fusion Maps from PET-CT Images of Lung Cancer,” *IEEE Trans. Med. Imaging*, vol. 39, no. 1, pp. 204–217, 2020, doi: 10.1109/TMI.2019.2923601.
- [66] L. Chen *et al.*, “Multi-Modality Attention-Guided Three-Dimensional Detection of Non-Small Cell Lung Cancer in 18F-FDG PET/CT Images,” *IEEE Trans. Radiat. Plasma Med. Sci.*, vol. 7311, no. c, pp. 1–1, 2021, doi: 10.1109/trpms.2021.3072064.
- [67] “Positron Emission Tomography (PET) Scan,” *St Jusde Children’s Research Hospital*, 2018. <https://together.stjude.org/en-us/diagnosis-treatment/imaging-tests/pet-scans.html>.
- [68] Pedro Domingos, “A Few Useful Things to Know About Machine Learning,” *Commun. ACM*, vol. 55, no. 10, pp. 79–88, 2012, [Online]. Available: <https://dl.acm.org/citation.cfm?id=2347755>.
- [69] Z. Hu, J. Tang, Z. Wang, K. Zhang, L. Zhang, and Q. Sun, “Deep learning for image-based cancer detection and diagnosis – A survey,” *Pattern Recognit.*, vol. 83, pp. 134–149, 2018, doi: 10.1016/j.patcog.2018.05.014.
- [70] S. Rajaraman, L. R. Folio, J. Dimperio, P. O. Alderson, and S. K. Antani, “Improved Semantic Segmentation of Tuberculosis—Consistent Findings in Chest X-rays Using Augmented Training of Modality-Specific U-Net Models with Weak Localizations,” *Diagnostics*, vol. 11, no. 4, p. 616, 2021, doi: 10.3390/diagnostics11040616.
- [71] S. Jaeger, S. Candemir, S. Antani, Y.-X. J. Wang, P.-X. Lu, and G. Thoma, “Two public chest X-ray datasets for computer-aided screening of pulmonary diseases,” *Quant. Imaging Med. Surg.*, vol. 4, no. 6, pp. 475–477, 2014, doi: 10.3978/j.issn.2223-4292.2014.11.20.
- [72] T. Rahman *et al.*, “Reliable tuberculosis detection using chest X-ray with deep learning, segmentation and visualization,” *IEEE Access*, vol. 8, pp. 191586–191601, 2020, doi: 10.1109/ACCESS.2020.3031384.
- [73] M. E. H. Chowdhury *et al.*, “Can AI Help in Screening Viral and COVID-19 Pneumonia?,” *IEEE Access*, vol. 8, pp. 132665–132676, 2020, doi: 10.1109/ACCESS.2020.3010287.
- [74] S. R. Wang X, Peng Y, Lu L, Lu Z, Bagheri M, “ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases,” *IEEE CVPR*, 2017.

- [75] J. Shiraishi *et al.*, “Development of a digital image database for chest radiographs with and without a lung nodule: Receiver operating characteristic analysis of radiologists’ detection of pulmonary nodules,” *Am. J. Roentgenol.*, vol. 174, no. 1, pp. 71–74, 2000, doi: 10.2214/ajr.174.1.1740071.
- [76] M. Dixit, A. Tiwari, H. Pathak, and R. Astya, “An overview of deep learning architectures, libraries and its applications areas,” *Proc. - IEEE 2018 Int. Conf. Adv. Comput. Commun. Control Networking, ICACCCN 2018*, pp. 293–297, 2018, doi: 10.1109/ICACCCN.2018.8748442.
- [77] A. Abubakar, M. Ajuji, and I. U. Yahya, “Comparison of deep transfer learning techniques in human skin burns discrimination,” *Appl. Syst. Innov.*, vol. 3, no. 2, pp. 1–15, 2020, doi: 10.3390/asi3020020.
- [78] X. Kang, B. Song, and F. Sun, “A deep similarity metric method based on incomplete data for traffic anomaly detection in IoT,” *Appl. Sci.*, vol. 9, no. 1, 2019, doi: 10.3390/app9010135.
- [79] A. Nasiri, A. Taheri-Garavand, and Y. D. Zhang, “Image-based deep learning automated sorting of date fruit,” *Postharvest Biol. Technol.*, vol. 153, pp. 133–141, 2019, doi: 10.1016/j.postharvbio.2019.04.003.
- [80] G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov, and N. Srivastava, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting,” *J. Mach. Learn. Res.*, vol. 15, no. 1, pp. 1929–1958, 2014, [Online]. Available: <http://jmlr.org/papers/v15/srivastava14a.html>.
- [81] S. Bharati, P. Podder, and M. R. H. Mondal, “Hybrid Deep Learning for Detecting Lung Diseases from X-ray Images,” *Informatics Med. Unlocked*, p. 100391, 2020, doi: 10.1016/j.imu.2020.100391.
- [82] S. Usama, S. Safwan, K. Bukhari, A. Syed, and S. Sajid, “The evaluation of convolutional neural network (CNN) for the assessment of chest X-ray of COVID-19 patients,” *Ann. Clin. Anal. Med.*, vol. 11, no. 6, 2020, doi: 10.4328/acam.20175.
- [83] N. Ansari, A. R. Faizabadi, S. M. A. Motakabber, and M. I. Ibrahimy, “Effective Pneumonia Detection using Res Net based Transfer Learning.”
- [84] J. Amores, “Multiple instance classification: Review, taxonomy and comparative study,” *Artif. Intell.*, vol. 201, pp. 81–105, 2013, doi: 10.1016/j.artint.2013.06.003.

- [85] S. Kikkiseti, J. Zhu, B. Shen, H. Li, and T. Q. Duong, “Deep-learning convolutional neural networks with transfer learning accurately classify COVID-19 lung infection on portable chest radiographs,” vol. 2019, no. December 2019, pp. 1–13, 2020, doi: 10.7717/peerj.10309.
- [86] M. Schultheiss *et al.*, “A robust convolutional neural network for lung nodule detection in the presence of foreign bodies,” *Sci. Rep.*, vol. 10, no. 1, 2020, doi: 10.1038/s41598-020-69789-z.
- [87] T. Rahman *et al.*, “Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images,” *Comput. Biol. Med.*, vol. 132, 2021, doi: 10.1016/j.compbimed.2021.104319.
- [88] D. Kermany, “Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images,” *Mendeley Data*, vol. 3, 2018.
- [89] J. Peng *et al.*, “Residual convolutional neural network for predicting response of transarterial chemoembolization in hepatocellular carcinoma from CT imaging,” *Eur. Radiol.*, vol. 30, no. 1, pp. 413–424, 2020, doi: 10.1007/s00330-019-06318-1.
- [90] D. Jakobovitz, R. Giryas, and M. R. D. Rodrigues, “Generalization Error in Deep Learning,” *Appl. Numer. Harmon. Anal.*, no. August, pp. 153–193, 2019, doi: 10.1007/978-3-319-73074-5_5.
- [91] T. Balaiah, T. J. T. Jeyadoss, S. S. Thirumurugan, and R. C. Ravi, “A deep learning framework for automated transfer learning of neural networks,” *Proc. 11th Int. Conf. Adv. Comput. ICoAC 2019*, pp. 428–432, 2019, doi: 10.1109/ICoAC48765.2019.246880.
- [92] D. Berrar, “Cross-validation,” *Encycl. Bioinforma. Comput. Biol. ABC Bioinforma.*, vol. 1–3, no. April, pp. 542–545, 2018, doi: 10.1016/B978-0-12-809633-8.20349-X.
- [93] Simonyan Karen and Zisserman Andrew, “Very deep convolutional networks for large-scale image recognition,” *3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc.*, 2015, [Online]. Available: <http://www.robots.ox.ac.uk/>.
- [94] P. Naveen and B. Diwan, “Pre-trained VGG-16 with CNN architecture to classify X-Rays images into normal or pneumonia,” *2021 Int. Conf. Emerg. Smart Comput. Informatics, ESCI 2021*, pp. 102–105, 2021, doi: 10.1109/ESCI50559.2021.9396997.

- [95] Y. Zhang, J. Gao, and H. Zhou, "Breeds Classification with Deep Convolutional Neural Network," *ACM Int. Conf. Proceeding Ser.*, pp. 145–151, 2020, doi: 10.1145/3383972.3383975.
- [96] Z. P. Jiang, Y. Y. Liu, Z. E. Shao, and K. W. Huang, "An improved VGG16 model for pneumonia image classification," *Appl. Sci.*, vol. 11, no. 23, 2021, doi: 10.3390/app112311185.
- [97] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2016-Decem, pp. 770–778, 2016, doi: 10.1109/CVPR.2016.90.
- [98] A. Agarwal, K. Patni, and D. Rajeswari, "Lung Cancer Detection and Classification Based on Alexnet CNN," *Proc. 6th Int. Conf. Commun. Electron. Syst. ICCES 2021*, pp. 1390–1397, 2021, doi: 10.1109/ICCES51350.2021.9489033.