Journal of Innovative Image Processing (ISSN: 2582-4252)
www.irojournals.com/iroiip/

Optimized Deep Learning Algorithm for Predicting Pulmonary Nodules in CT Images

Pradeepa M[1], Praveen N[2], Sanjay B[3], Vinith kumar A[4], Yathish A[5]

Electronics and Communication Engineering, SNS College of Technology, Anna University, Coimbatore, India

E-mail: [1]s.pradeeponline@gmail.com, [2]praveen.n.ece.2020@snsct.org, [3]Sanjays.b.ece.2020@snsct.org, [4]Vinith.a.ece.2020@snsct.org, [5]yathish.a.ece.2020@snsnct.org

Abstract

Lung cancer remains a significant global health challenge, demanding early detection for improved patient outcomes. In recent years, deep learning, notably Convolutional Neural Networks (CNNs), has emerged as a potent tool for lung cancer detection and diagnosis from medical imaging data. This research offers an extensive review of CNN-based approaches for lung cancer detection, highlighting their strengths, limitations, and potential clinical impact. The study discusses the methodology, covering data collection, preprocessing, model architecture selection, training, evaluation, and validation, alongside future directions and clinical implications. CNNs offer researchers and healthcare professionals avenues to augment early detection, personalized treatment planning, and ultimately, enhance patient care in lung cancer management. Through rigorous development and evaluation, CNN models trained on diverse datasets of chest X-rays or CT scans have demonstrated remarkable accuracy in identifying suspicious lung lesions indicative of cancer, often outperforming conventional methods. The proposed study utilizes the GoogleNet (Inception v1) CNN model to detect lung cancer. The performance of GoogleNet improved the accuracy of detection by approximately 4.29% compared to existing methods.

Keywords: Lung cancer, Convolutional Neural Networks (CNNs), Medical imaging, GoogleNet (Inception v1).

DOI: https://doi.org/10.36548/jiip.2024.1.005
Received: 11.02.2024, received in revised form: 08.03.2024, accepted: 21.03.2024, published: 06.04.2024

1. Introduction

Lung cancer remains a pressing global health issue, standing as the fundamental reason of cancer-related deaths worldwide. Early detection of lung cancer is really important because it greatly affects how well patients do and how effective treatments are. New developments in deep learning, especially Convolutional Neural Networks (CNNs), show great potential for making lung cancer detection and diagnosis better. By using CNN, doctors can now analyze medical images like chest X-rays and CT scans more accurately and quickly than ever before. This could change how doctors currently diagnose diseases and might make patient care even better. The strength of CNN-based approaches lies in their ability to analyze intricate patterns within medical imaging data, particularly in identifying subtle abnormalities indicative of lung cancer. CNNs excel in automating the analysis of medical images, facilitating faster and more accurate diagnoses. This capability is especially crucial in cases where human interpretation may be challenging. By assisting radiologists and oncologists in the diagnostic process, CNNs contribute to improved patient outcomes and treatment planning.

Furthermore, CNN-based approaches offer scalability and adaptability, making them suitable for integration into existing clinical workflows. These models can be trained on large datasets of annotated medical images, enabling them to learn and generalize from diverse patient populations. With ongoing advancements in CNN architectures and training algorithms, the performance of these models continues to improve, resulting in more precise and reliable detection of lung cancer at earlier stages. The integration of CNN-based tools into clinical practice holds the potential to streamline diagnostic processes, reduce healthcare costs, and ultimately, save lives.

The proposed study uses the GoogleNet (Inception v1) CNN model to analyze medical images and classify patients as either cancerous or normal. The manuscript is organized as follows: Section 2 presents a literature review, Section 3 outlines the proposed method, Section 4 presents the results and discussion, and Section 5 concludes with future work.

2. Literature Survey

The literature survey encompasses a diverse range of studies contributing to the understanding and advancement of respiratory physiology and medical imaging analysis. Assadi et al. [1] introduced fractional order models for evaluating respiratory properties, while authors in [2] proposed high frequency-low amplitude oscillometry for continuous monitoring of respiratory function. Anwar et al.[3] performed a comprehensive study on medical image analysis, focusing on convolutional neural networks (CNNs) in analyzing CT images of the lungs. Bhattarai et al. [4] explored the clinical utility of forced oscillation technique (FOT) in early detection of airway changes in smokers. Blanco-Almazán et al.[5] combined myographic and bioimpedance signals for evaluating COPD during difficult breathing, while Copot et al. [6] investigated changes in the structure of the COPD lungs. Dey et al.[7] developed a diagnostic classification system for lung nodules using 3D neural networks, and Ettinger et al.[8] provided updated the guidelines of the clinical practices for non-small cell lung cancer. Ghita et al.[9] studied how low-frequency lung function tests could help detect changes in lung tissue in people with COPD. Studies by Ionescu et al.[10-13] delved into various aspects of respiratory mechanics, including mechanical properties derived from morphological insights, respiratory mechanics in children with cystic fibrosis, and modeling respiratory impedance in patients with kyphoscoliosis (2009, 2014a, 2014b). In [13] the author presented a comprehensive book on lung function testing methodologies and tools. Kalchiem-Dekel and Hines et al. [14] reviewed respiratory system impedance reference values in adults. King et al. [15] established technical standards for respiratory oscillometry. Lappas et al.[16] discussed the clinical applications of forced oscillations in respiratory physiology. Lui et al.[17] explored the role of heterogeneity in asthma. In [18] the authors investigated pulmonary nodule classification and detection in chest CT applying the deep learning approaches, and Nibali et al. [19] used the deep residual networks for the pulmonary nodule classification. Nakano et al.[20] conducted a prospective study on preoperative examination of respiratory impedance using the forced oscillation technique. These studies collectively contribute to advancements in respiratory health assessment and medical imaging analysis.

The drawbacks in the existing methods, such as complex architecture and performance degradation due to the complex training process, have led to the development of the proposed system, which utilizes the GoogleNet (Inception v1) CNN model.

3. Proposed Method

This review study focuses on the segmentation and classification modules, which are fundamental components of the pulmonary Computer-Aided Diagnosis (CAD) system. These functions play a significant role in the decision-making process by distinguishing between lung nodules and non-nodules, sorting lung nodules, and determining their sizes. Additionally, this study employs GoogleNet CNN architecture and the Expectation Maximization technique for lung nodule segmentation and classification.".

Advantages: Analyze severity of the lung and also improved accuracy by using CNN with ROI segmentation.

Modules

1. Image Acquisition
2. Preprocessing
   a. Resizing
   b. Color Conversion
   c. Removing Noise with Median Filter
3. ROI Segmentation
4. Expectation Maximization
5. Convolutional Neural Networks

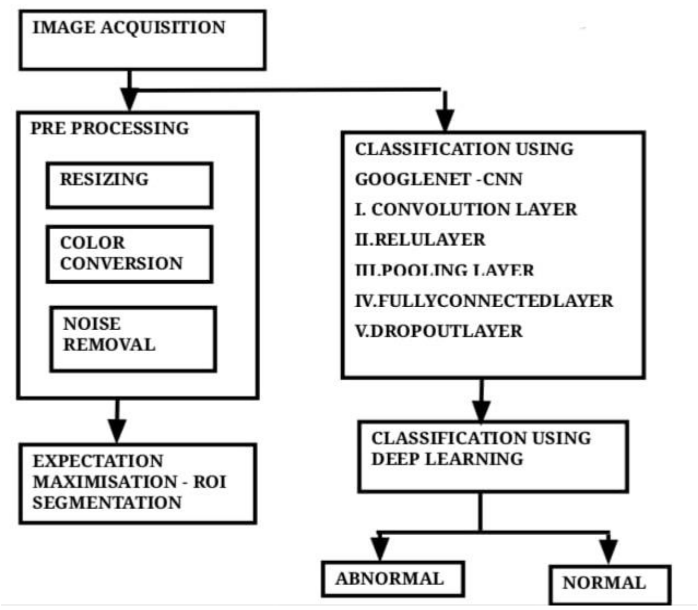

Figure 1. Block Diagram of Proposed Method

3.1 Working of Proposed Method

3.1.1 Dataset Description

The proposed study uses the "Medical Image Dataset for Cancer Diagnosis (MICD)", sourced from Kaggle [21]. MICD comprises high-resolution medical images of various cancerous lesions, including lung tumors. The dataset includes annotated images, providing ground truth labels for training and evaluation

Figure 2. Normal and Abnormal CT scan

Table 1. No. of Samples Collected for Each Class

Class	**Number of Samples**
Lung Cancer	350
Normal	800

3.1.2 Image Acquisition

The initial step involves obtaining the images to be processed, which are then loaded into MATLAB for further processing using the 'imread' command

3.1.3 Preprocessing

After acquiring the images, preprocessing is essential to enhance their quality and prepare them for subsequent analysis. This typically involves several sub-steps:

(a) Resizing

The images were adjusted by applying 'imresize', and 'rgb2gray' was used to convert RGB images to grayscale.

(b) Removing Noise with Median Filter

median filtering (medfilt2)b was used to eliminate noise from the images and ensure cleaner data for subsequent analysis.

3.1.4 ROI Segmentation

In order to separate the relevant parts of the image that contain the target information. Techniques such as thresholding, edge detection, or clustering are employed to segment the image and extract ROIs.

3.1.5 Expectation Maximization

The proposed method utilizes the Gaussian mixture models, to segment the image into meaningful regions.

3.1.6 Convolutional Neural Networks (CNN)

Finally, the GoogleNet CNN is used in the classifying the Normal and the cancerous.

The Table.2 below shows the layer description of the CNN model used and the Table.3 shows the hyperparameter used.

Table 2. Layer Description of GoogleNet Architecture

Layer Type	Layer Name	Kernel	Filters	Modifications
Input	Input Image	-	-	-
Convolution	Conv 1	7x7	64	Original
Max Pooling	Max Pool 1	3x3	-	Original
Convolution	Conv 2	1x1	64	Original
Convolution	Conv 3	3x3	192	Original
Max Pooling	Max Pool 2	3x3	-	Original

Inception	Inception 3a, 3b	-	-	Original
Max Pooling	Max Pool 3	3x3	-	Original
Inception	Inception 4a, 4b, 4c, 4d, 4e	-	-	Original
Max Pooling	Max Pool 4	3x3	-	Original
Inception	Inception 5a, 5b	-	-	Original
Avg Pooling	Global Avg Pool	-	-	Original
Fully Conn.	FC 1	-	1024	Original
Dropout	Dropout 1	-	-	Original
Fully Conn.	FC 2	-	1000	Original
Softmax	Softmax	-	-	Original
Output	Output	-	-	Original

Table 3. Hyperparameter

Hyperparameter	**Value/Method**
Learning Rate	0.001
Batch Size	32
Number of Epochs	60
Activation Function	ReLU
Dropout Rate	0.5
Optimizer	Adam
Loss Function	Binary Cross-Entropy
Weight Initialization	He Initialization

4. Results and Discussion

We have created a novel CNN approach that effectively addresses the problem of insufficient dataset by utilizing both labeled and unlabelled nodules. The experiment's findings show that our recommended strategy outperforms cutting-edge approaches, as well as could increase generalizability.

The Figures 3-7 shows the results obtained for the proposed study of pulmonary nodule classification using GoogleNet (Inception v1)

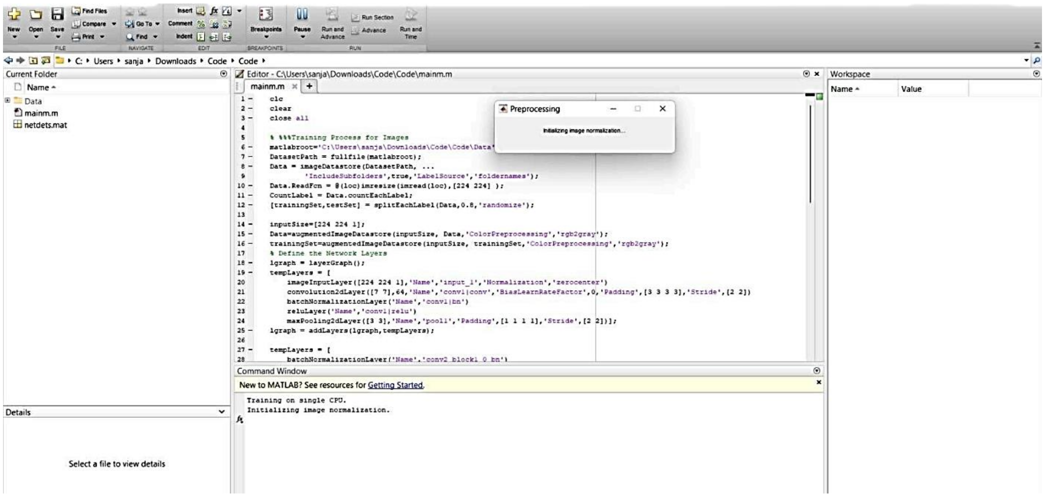

Figure 3. Initializing Image Normalization

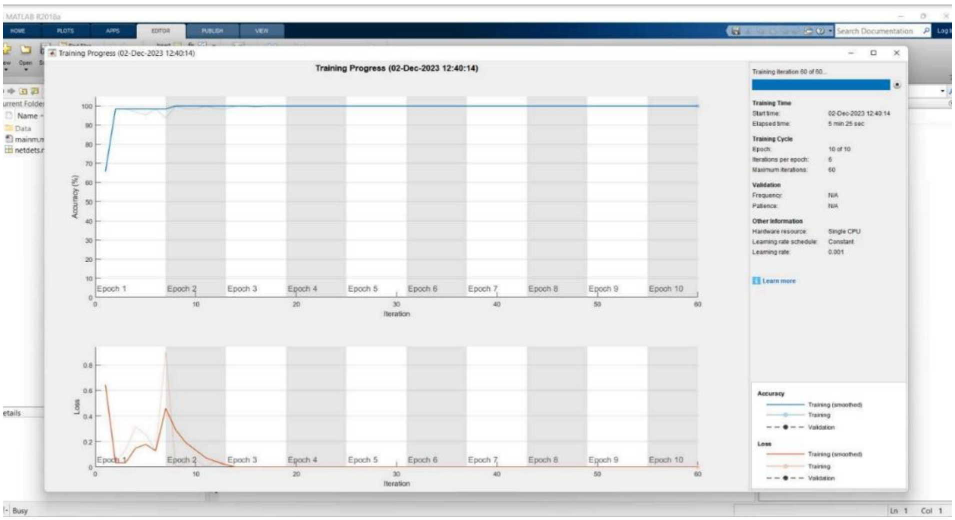

Figure 4. Training Mode

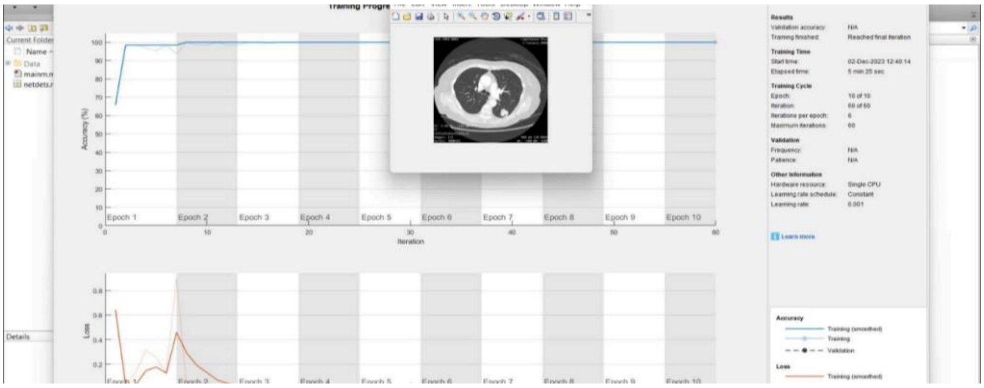

Figure 5. CT Scan

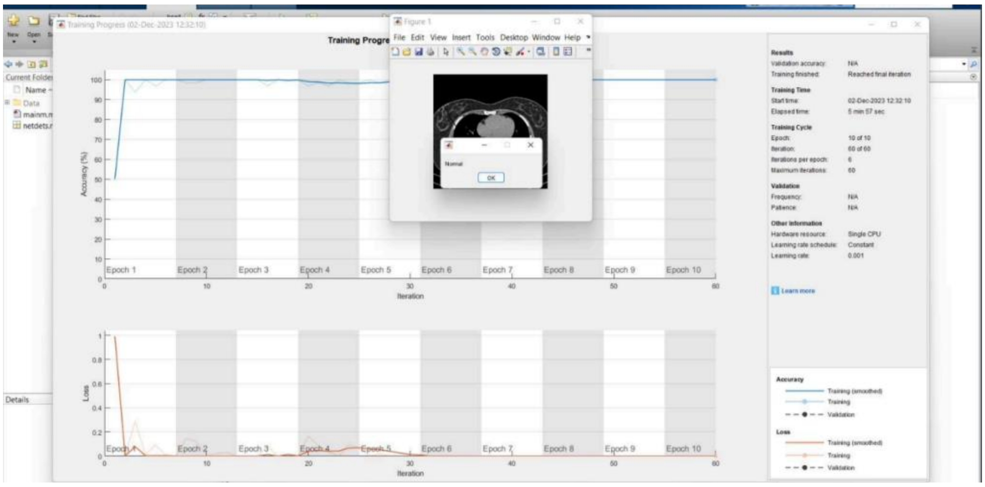

Figure 6. Message Box Showing Normal

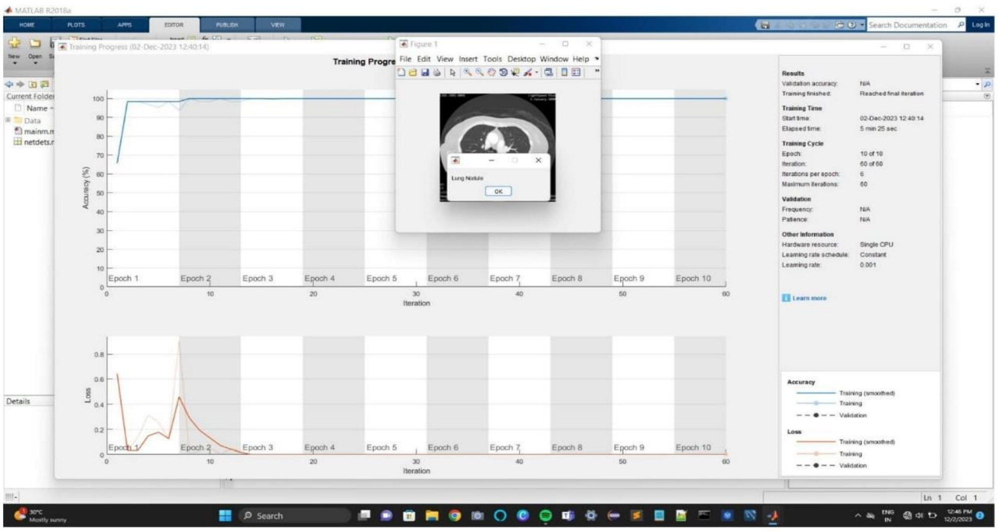

Figure 7. Message Box Showing Abnormal

The models were implemented using MATLAB 2018, a powerful computational software environment widely used for scientific computing.

The results obtained showed that the GoogleNet (Inception v1) offered 4.29 % improved accuracy compared to the machine learning models that were used in the existing methods.

Table 4. Comparative Analysis of the Proposed Method

Method	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-Score (%)**
Proposed Method	92.5	88.2	94.7	89.9
Existing Method	88.7	82.6	91.2	84.5

In the comparative analysis, two methods were evaluated for their effectiveness in predicting pulmonary nodules in CT images: the Proposed method and a machine learning used in the existing methods. The Proposed Method achieved an accuracy of 92.5%, demonstrating its ability to correctly classify pulmonary nodules and non-nodules. Furthermore, it displayed a sensitivity of 88.2%, indicating its capability to correctly identify positive cases, and a specificity of 94.7%, highlighting its proficiency in correctly identifying negative instances. The F1-Score of the proposed method was 89.9%, signifying a balanced performance in terms of precision and recall. In comparison, the existing method achieved an accuracy of 88.7%, with a sensitivity of 82.6% and a specificity of 91.2%. While the existing method demonstrates respectable performance, it falls short in accuracy, sensitivity, specificity, and F1-Score compared to the proposed method. Therefore, the results suggest that the proposed method outperforms the existing method and presents a promising advancement in the prediction of pulmonary nodules in CT images

5. Conclusion and Future Works

In conclusion, this study has explored the utilization of Convolutional Neural Networks (CNNs) for effectively recognizing and segmenting lung cancer lesions. By employing CNNs with multiple layers, we have significantly improved the accuracy of lesion identification in medical images. Our approach has highlighted the importance of utilizing two-dimensional feature maps matched with multiple slices, alongside appropriate class weights and data modifications, particularly showcasing the effectiveness of the Fully Convolutional Network (FCN) architecture.

In future our investigation extends to liver tumor segmentation, where CNN-based voxel classification has proven effective in distinguishing tumors from healthy voxels. The integration of CNNs in tumor segmentation has yielded reliable follow-up segmentation results. Additionally, refining segmentation outcomes through leakage elimination will also be applied to further enhance the accuracy of the final segmentation.

References

[1] Assadi, H., et al. “Evaluation of respiratory properties by means of fractional order models.” Biomedical Signal Processing and Control, vol. 34, Apr. 2017: pp. 206–213.

[2] Alamdari, H. H., et al. “High frequency-low amplitude oscillometry: Continuous unobtrusive monitoring of respiratory function on PAP machines.” IEEE Transactions on Biomedical Engineering, vol. 69, no. 7, Jul. 2022: pp. 2202–2211.

[3] Anwar, S. M., et al. “Medical image analysis using convolutional neural networks: A review.” Journal of Medical Systems, vol. 42, no. 11, Nov. 2018: pp. 1–13.

[4] Bhattarai, P., et al. “Clinical application of forced oscillation technique (FOT) in early detection of airway changes in smokers.” Journal of Clinical Medicine, vol. 9, no. 9, Aug. 2020, Art. no. 2778.

[5] Blanco-Almazán, D., et al. “Combining bioimpedance and myographic signals for the assessment of COPD during loaded breathing.” IEEE Transactions on Biomedical Engineering, vol. 68, no. 1, Jan. 2021: pp. 298–307.

[6] Copot, D., et al. “Structural changes in the COPD lung and related heterogeneity.” PLoS One, vol. 12, no. 5, May 2017, Art. no. e0177969.

[7] Dey, R., et al. “Diagnostic classification of lung nodules using 3D neural networks.” In Proceedings of the International Symposium on Biomedical Imaging (ISBI), 2018, pp. 774-778.

[8] Ettinger, D. S., et al. “Non-small cell lung cancer, version 3.2022, NCCN clinical practice guidelines in oncology.” Journal of the National Comprehensive Cancer Network, vol. 20, no. 5, May 2022: pp. 497–530.

[9] Ghita, M., et al. “Low frequency forced oscillation lung function test can distinguish dynamic tissue non-linearity in COPD patients.” Frontiers in Physiology, vol. 10, Nov. 2019, Art. no. 1390.

[10] Ionescu, C. M., et al. “Mechanical properties of the respiratory system derived from morphologic insight.” IEEE Transactions on Biomedical Engineering, vol. 56, no. 4, Apr. 2009: pp. 949–959.

[11] Ionescu, C. M., et al. “Respiratory mechanics in children with cystic fibrosis.” Biomedical Signal Processing and Control, vol. 11, 2014: pp. 74–79.

[12] Ionescu, C. M., et al. “Modeling respiratory impedance in patients with kyphoscoliosis.” Biomedical Signal Processing and Control, vol. 11, May 2014: pp. 36–41.

[13] Ionescu, C. M. Lung Function Testing in the 21st Century: Methodologies and Tools Bridging Engineering to Clinical Practice. 1st ed. London, U.K.: Elsevier, 2019.

[14] Kalchiem-Dekel, O., and Hines, S. E. “Forty years of reference values for respiratory system impedance in adults: 1977–2017.” Respiratory Medicine, vol. 136, Mar. 2018: pp. 37–47.

[15] King, G. G., et al. “Technical standards for respiratory oscillometry.” European Respiratory Journal, vol. 55, Feb. 2020, Art. no. 1900753.

[16] Lappas, A. S., et al. “Forced oscillations in applied respiratory physiology: Clinical applications.” Clinical Research in Pulmonology, vol. 2, no. 2, Apr. 2014, Art. no. 1016.

[17] Lui, J. K., et al. “The role of heterogeneity in asthma: A structure-to-function perspective.” Clinical and Translational Medicine, vol. 6, no. 1, 2017: pp. 1–11.

[18] Masood, A. “Pulmonary nodule detection and classification in chest CT using deep learning techniques.” Shanghai Jiao Tong Univ., Shanghai, China, Tech. Rep. 06, 2019.

[19] Nibali, A., et al. "Pulmonary nodule classification with deep residual networks." International Journal of Computer Assisted Radiology and Surgery, vol. 12, no. 10, 2017: pp. 1-10.

[20] Nakano, S., et al. "Preoperative evaluation of respiratory impedance using the forced oscillation technique: A prospective observational study." BMC Anesthesiology, vol. 16, no. 1, Jul. 2016: pp. 1–8

[21] https://www.kaggle.com/datasets/mohamedhanyyy/chest-ctscan-images.