Journal of Information Systems Engineering and Management
2025, 10(26s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Deep Learning-based Chest X-Ray Analysis for Early Lung Disease Detection

Indumathi R[1], Dr.R.Jayaraj[2], K. Oviyaa[3], B. Pavithra[4]

[1]*Department of Computer Science and Engineering, Manakula Vinayagar Institute of Technology, Puducherry. indumathicse@mvit.edu.in*

[2]*Department of Data Science and Business System, SRM Institute of Science and Technology, Chennai. jayarajr1@srmist.edu.in*

[3]*Department of Computer Science and Engineering, Manakula Vinayagar Institute of Technology, Puducherry. koviyaa2004@gmail.com*

[4]*Department of Computer Science and Engineering, Manakula Vinayagar Institute of Technology, Puducherry. pavithrabalaji136@gmail.com*

ARTICLE INFO

Received: 22 Dec 2024

Revised: 14 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Pulmonary conditions, like lung cancer, tuberculosis, covid-19, pneumonia (bacterial and viral) and other conditions, like normal lungs, impact the respiratory system, respiratory disorders and oxygen metabolism. Pulmonary conditions can lead to symptoms like cough, shortness of breath and chest pain, usually necessitating medical visualization (X -ray of chest and computed tomography) for diagnosis and follow-up. To enhance lung disease categorization, a hybrid AI model that integrates Capsule Neural Networks (Caps Net) and the VGG19 architecture is suggested. Caps Net is used to extract spatial hierarchies in images, realizing the interrelation between various features and minimizing the chances of misclassification. This is especially beneficial in medical visualization where image interrelation is crucial for proper diagnosis. A profound, sticky neural network, VGG19 boosts sine extraction and enables the model to inspect images more intensely. This is a combination of the two models' strength in order to ease the process of classification and enhances the accuracy of prediction, enabling more types of diseases like bacterial pneumonia, viral pneumonia, and crown viruses to be covered. Computer algorithms give a safer and more exact approach to diagnosing lung illness, particularly early on. Notebooks are complex relationships of pictures, with capabilities for multi-bourton recognition and consideration for the limitations of present medical imagery techniques.

Keywords: Detection for various dysentery, image classification, early diagnosis, prediction accuracy, lung cancer, tuberculosis.

INTRODUCTION

Lung disease is a broad term for the numerous disorders that occur in the respiratory system and threaten its capacity to function in its best form. The disorders are classified under several categories, such as chronic obstructive pulmonary disease (MPOC), asthma, infection, interstitial pulmonary disease, and lung cancer. COPD defined as chronic pulmonary disease that involves long-term respiratory symptoms and constricted airflow. In effect, COPD resulting from long-term impact of inflammation like cigarette smoke encompasses conditions like chronic bronchitis and emphysema. Individuals with COPD tend to have shortness of breath, persistent cough, and heightened risk to respiratory infections. ASTMA is an inflammatory respiratory disease of chronic nature, accompanied by recurring episodes of wheezing, breathing, chest embarrassment and cough. Triggers like allergens and stimuli can trigger exacerbation of asthma. Management typically consists of bronchodilators and anti-inflammatory medication to manage symptoms and enhance air flow. Infections, like pneumonia and bronchitis, are normally attributed to bacteria, viruses or fungi. These infections can result in inflammation of pulmonary tissues, leading to symptoms like fever, cough and shortness of breath. In the majority of instances, by virtue of the role of antibiotics in combating bacterial infections, early diagnosis and correct treatment are crucial towards curing these diseases. Interstitial lung disease encompasses a wide range of conditions that impact pulmonary interference - tissues giving support to airbags. Diseases such as idiopathic pulmonary fibrosis (IPF) entail fibrosis of lung tissue, causing stiffness and diminishing lung function. These conditions tend to be difficult to diagnose and treat, necessitating a multidisciplinary management for optimal care. Lung cancer arises when lung cells do not regulate abnormally. The primary risk factor is smoking, but the action of other carcinogens may also cause it. Early diagnosis by screening and effectiveness in treatment modalities, such as surgery, chemotherapy and immunotherapy, enhanced the outcome for a few individuals with lung cancer. Therefore, lung diseases encompass a variety of conditions that impact the respiratory function, ranging from chronic and progressive illnesses, like COP and asthma, to infectious and interstitial lung diseases, as well as a serious issue of lung cancer. Early diagnosis, proper treatment, and dietary changes are significant factors in the prevention of such diseases from taking a toll on respiratory well-being.

RELATED WORK

This Pneumonia remains a significant global health challenge, particularly among vulnerable populations such as children and the elderly. According to recent studies, early diagnosis and timely intervention are crucial in reducing pneumonia-related mortality [1]. AI-based diagnostic tools are playing a key role in improving accuracy and facilitating faster medical decisions.

This study examines the epidemiology and risk factors of pneumonia, emphasizing the role of technological advancements in identifying patterns of disease progression. [2] Machine learning techniques are proving instrumental in analyzing patient data, enabling more effective treatment approaches.

Reports indicate that pneumonia could result in millions of child deaths by 2030 if better healthcare strategies are not implemented. [3] The introduction of AI-driven imaging solutions and diagnostic models can significantly improve early detection, particularly in regions with limited healthcare resources.

A study on pneumonia among older adults highlights the importance of early intervention and accurate diagnosis [4]. AI-based image analysis tools have shown promising results in assisting radiologists by improving detection rates and reducing misinterpretation errors.

In addition to infectious diseases, environmental factors such as air pollution contribute to an increased risk of pneumonia. Studies suggest that prolonged exposure to pollutants exacerbates respiratory diseases, [5] making AI-enhanced imaging crucial for identifying pollution-induced lung abnormalities. Research on COVID-19 pneumonia has underscored the necessity of AI-driven diagnostic approaches. AI models have demonstrated their ability to distinguish between [6] COVID-19 related pneumonia and other lung infections, thereby improving clinical outcomes and reducing diagnostic errors.

The classification of viral pneumonia remains a challenge due to overlapping symptoms with bacterial infections. AI models trained on diverse datasets can assist in [7] differentiating between various pneumonia types, ensuring that patients receive appropriate treatment. Traditional diagnostic methods such as CT scans and chest X-rays are widely used for pneumonia detection. However, human errors and limitations in image interpretation often lead to inaccurate diagnoses [8]. AI-powered tools address these concerns by enhancing image analysis precision and automating disease classification.

Comparative studies on the effectiveness of chest X-rays versus CT scans for pneumonia detection highlight discrepancies in diagnostic accuracy [9]. AI-driven systems trained on large imaging datasets can help standardize diagnostic practices and support clinicians in making well-informed decisions.

Advances in medical imaging techniques, including MRI and X-ray, have transformed pneumonia diagnosis [10]. AI-enhanced tools bridge the gap between imaging modalities by improving interpretation efficiency, ensuring better diagnostic outcomes for patients.

The role of imaging in pneumonia diagnosis has been extensively studied. The Diagnostic Imaging Center [11] provided insights into various imaging techniques used for pneumonia detection, emphasizing the importance of MRI and high-resolution CT scans in improving diagnostic accuracy. [12] examined the pathology and treatment of viral pneumonia, differentiating it from bacterial pneumonia and discussing specific treatment approaches. Klein et al. [13] reviewed current treatment strategies for COVID-19 pneumonia, highlighting emerging therapies and best practices for clinical management.

PROPOSED METHODOLOGY

The system proposed incorporates capsules and VGG19 networks to enhance the detection of lung disease from medical imaging. Capsular Networks preserves a space hierarchy and captures the function orientation and interconnections, whereas VGG19 is particularly good at trustworthy extraction of chest x-ray signs. This hybrid technique enhances diagnostic accuracy and generalizability, even with limited data, and can detect diseases like Bacterial Pneumonia, Viral Pneumonia, Lung Cancer, COVID-19 and Normal lung health. With fewer false negatives and positives, the system provides faster, more accurate predictions, assisting radiologists to make proper decisions and improve patient care.

A. CAPSULE NETWORKS (CAPSNETS):

Capsule networks (CapsNets) are an architecture of neural networks that are meant to solve some of the issues with standard convolutional neural networks (CNNSs), specifically spatial relationships and equality (the capacity to identify objects independently of orientation). CAPSNETS encloses the full object's pose data (position, orientation, size) as vectors instead of scalar values, unlike CNNS [10]. A capsule is a collection of neurons that emit vectors instead of scalars, which essentially change the manner in which neural networks read data. In standard neural networks, the neurons exhibit scalar values. This shows the occurrence of a specific feature (e.g. textures and edges) [3]. Conversely, the vector output of the capsule conveys much more elaborate information. A vector's length represents the probability of an object or its part appearing in the image. A short vector indicates a less likely presence of a feature, while a longer vector indicates a higher probability of its existence. More importantly, the orientation of the vector provides \ "pos -information, \", such as position, rotation, scale and even prospect. This enables the network to identify objects and their purpose across different configurations, orientations and location in space, giving a richer description of the object in the image. Dynamic routing is an operation that binds capsules to a different level within the capsule network. In contrast to standard CNNs, which tend to utilize the maximum number to compress spatial information for upper levels, capsule networks rely on dynamic routing to preserve spatial relationships and achieve a more accurate interpretation of the object's parts and their structure. With dynamic routing, low-level capsules project output vectors to upper-level capsules based on high-level prediction agreements and capsule output. This is an iterative process. Capsules pass on more conclusions to higher-level capsules [3]. This is suitable for prediction. This selective relation between capsules means that the information that passes through is information that is necessary and relevant to pass on while retaining the object's hierarchical and spatial information, which results in better processing of recognition and transformation.

i. CAPSULE OUTPUT:

The output of capsule is a vector computed as:

$$V_j = \frac{||S_j||^2}{1 + ||S_j||^2} \frac{S_j}{||S_j||}$$

Where,

- S_j - capsule j input (balanced summation of low-level capsules).
- V_j - output vector(capsule j)
- $|| S_j ||$-Vector value (or standard)
- S_j is the activation level.

This non-linear compression operation guarantees that the length of the output vector lies between 0 and 1. In this case, a shorter vector implies a lower probability, while a longer vector means the existence of a function represented by a capsule.

j. *ROUTING BY AGREEMENT*:

Predictive exit from capsule I to capsule J:

$$\widehat{u_{j|i}} = W_{ij} u_i$$

Where,

- u_i is the output Vector from Capsule i.
- W_{ij} is the weight matrix between capsule i and capsule j.
- $\hat{U}_{j|i}$ is the prediction of capsule i for capsule j.

The match is made by the scalar product between the predicted output $\hat{u}_{j|i}$ and the output v_j of the capsule in the next layer.

$$a_{ij} = \widehat{u_{j|i}} . v_j$$

Dynamic routing allows a lower-level capsule (Layer I) to pass its output to a higher-level capsule (Layer J) according to the agreement between the higher-level capsule's predicted output and actual output. During this routing, weights of repeated elements are scaled based on this agreement. The connection weights among capsules are then updated accordingly—i.e., [1] the more the influence of a lower-level capsule on a higher-level capsule, the closer their connection.

RESULT AND DISCUSSION

a. DATA COLLECTION:

The information used to predict lung disease were acquired from the Kaggle dataset through open source [dataset] by lung disease (type 4) (https://www.kaggle.com/datasets/mkarmanohardalvi/poumer-difficulé-datase-4-cy). The dataset contains images of chest x-rays, representative of four states of lung disease: lung cancer, tuberculosis, pneumonia and COVID-19. The dataset is used to develop machine learning models designed to classify the diseases according to the features of radiographic images. Every image has gone through a pretreatment phase for enhancing quality and consistency. Specifically, there is data growth that enhances resizing, standardization, and resilience and processing of the model. Function extraction was performed using deep architectures of the neural network, [8] like the VGG19 model and the capsule networks, which facilitate capturing both fine and spatial details. The integration of these architectures delivers accurate identification of the pulmonary disease type, retaining details, i.e., orientation of the image, shape and texture. Having been trained, the model was tested on new unseen data for predicting the disease type from new X-ray images to assist in early and precise diagnosis of lung disease.

b. PRE-PROCESSING AND FEATURE EXTRACTION:

Preprocessing and element extraction is a critical process in the operation of pulmonary disease prediction, readying the dataset for proper establishment of the model. In preprocessing, raw trunks' x-ray images in the dataset are normalized to enhance quality and suit depth learning models. This takes a number of steps, including resizing images of consistent resolution. This helps to make all input data equal in the model. Techniques like standardization are also used to large scale pixel values from 0 to 1 as rules, eradicating changes in intensity and enhanced contrast, making signs of interest more conspicuous. It further employs data-enhancing techniques like coups, rotations, and scaling to artificially enlarge the dataset, rendering the model more accurate for orientation and image scale modifications [10]. Once preprocessing is done, the extraction of the elements starts. Here, we employ sophisticated neural network architectures like VGG19 and capsule networks to extract significant features from the image. VGG19 can identify fine-grained particles like edges and texture very well via deep convolutional layers, while capsule networks ensure that spatial hierarchy relationships and varied properties of the lung, e.g., its shape and structure, are kept intact. Combining these processes enables models to identify intricate models and variations typical of many forms of lung diseases, which in turn enables prediction to be highly accurate and consistent.

c. MODEL CREATION:

The pulmonary disease forecasting model was developed by integrating the powers of VGG19 and capsule networks to leverage their individual potential in sign extraction and preservation of spatial relations [5]. VGG19, a deep neural network, served as the primary extractor. Its several convolutional layers are made to extract fine-grain features like edges, textures and shapes in thoracic X-rays. By running the pre-treated images through the VGG19 architecture, dense hierarchical features describing pulmonary anatomy and disease models are obtained. VGG19, however, is not sufficient to cope with spatial variations such as rotations or viewpoint changes. To overcome this shortcoming, Capsule Networks were incorporated into the model. Capsular networks preserve space hierarchies and are capable of identifying objects and models in any orientation, making them well-suited to medical images, where organs might be in any position. The output of VGG19 is put under capsule networks, which apply a dynamic routing so that only the right functions are moving forward, [3] elucidating the comprehension of the spatial features of the disease. This hybrid approach makes sure that the model not only learns accurate features of lung diseases but also learns their spatial relations, leading to more accurate and stable predictions of diseases like lung cancer, tuberculosis, pneumonia, and COVID-19. The model is trained and validated on the labeled dataset, and later it can process and predict lung diseases from new X-ray images.

d. ACCURACY:

Accuracy is the ratio of the number of instances correctly predicted (true positives and true negatives) to the total number of instances. Accuracy gives an idea of how accurate the model is overall, but it is misleading on an unbalanced data set.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Number\ of\ Instances}$$

Where,

- **True Positive (TP):** The actual case was classified rightly.
- **True Negative (TN):** Correctly predicted casement.
- Total samples: all actual positive results, true negatives, false works, false negatives.

Total True Positives (TP) = 282 + 399 + 352 + 263 + 135 = 1431

Total Instances = 1748

$$Accuracy = \frac{1431}{174} = 0.82$$

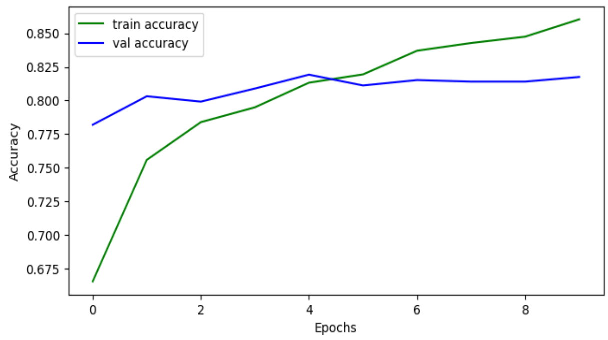

Figure 1: Accuracy Graph

e. PRECISION:

A Precision is a performance metric in classification models to assess positive forecast accuracy. In particular, he computes the ratio of true positive forecasts to all cases forecast as positive. That is, precision gives a response to the question:

"Of all cases predicted by the model, was positive, how much was actually positive?"

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Where,

True Positives (TP): Cases where the model correctly predicts the positive class.

False Positives (FP): Cases where the model incorrectly predicts a positive result when it should have been negative.

Here,

For class 0: TP=280, FP=115

$$Precision = \frac{280}{280 + 115} = 280 = 0.71$$

f. RECALL:

Reminders or true positive/sensitivity rates are some of the most important performance measures for classification models. Gauge how well a model can identify all positive actual instances of the data set.[10] Specifically, reminders solve all the real positive cases questions. For instance, if it is detected that there is a disease or the fraud is recognized, in cases where there isn't a positive case (false negative) is costly, and solves how the model properly identifies this.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

Where,

- **True Positive (TP):** Occurs when the model correctly predicts a positive class.
- **False Negative (FN):** Occurs when the model incorrectly classifies a positive instance as negative.

Here,

$$Recall = \frac{280}{280+132} = 0.68$$

High recall means the model does well on classifying most actual positive cases and keeps the number of false negatives to a minimum. [10] It often, however, comes with high reminder to the loss of precision since the model may assign more false positives so that it has the potential to catch more actual positive points. [8]Accordingly, the review is particularly beneficial when it is vitally essential to reduce the possibility of failing to detect any positives, although there may be false negatives wrongly classified. Review is usually looked at with accuracy while considering more balanced performance estimation by using the F1 measure [6].

g. F1 SCORE:

The F1 score is the harmonic mean of precision and recall. It provides a single metric that balances both accuracy and feedback, making it especially useful for imbalanced datasets.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

F1 scores are between 0 and 1, with 1 being the maximum score, which represents high accuracy and recall. Loss (or cost) is a function that measures the difference between the predicted and actual values when training the model. It directs the optimization process to enhance the model. The most popular loss functions for classification and regression are.

$$F1\ Score = 2 \times \frac{0.71 \times 0.68}{0.71+0.68} = 2 \times 0.3474 \quad = 0.69$$

Table 1: Class-wise Evaluation Metrics

Class	Precision	Recall	F1 Score	Support
0	0.71	0.68	0.69	414
1	0.95	0.96	0.95	416
2	0.92	0.89	0.90	396
3	0.63	0.68	0.65	387
4	1.00	1.00	1.00	135

Precision	-	-	0.82	1748
Macro Average	0.84	0.84	0.84	1748
Weighted Average	0.82	0.82	0.82	1748

Cross –Entropy Loss(For Classification):

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log(p_i\ ) + (1-y_i)\log(1-p_i)]$$

Where,

- y_i -real label (1 in case of being positive, 0 in case of being negative).
- p_i - plus class planned probability.
- N = total number of instances.

Mean Squared Error(for regression):

$$\text{MSE loss}=\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Where,

- y_I is the actual value
- $\hat{y}_i$ is the predicted value

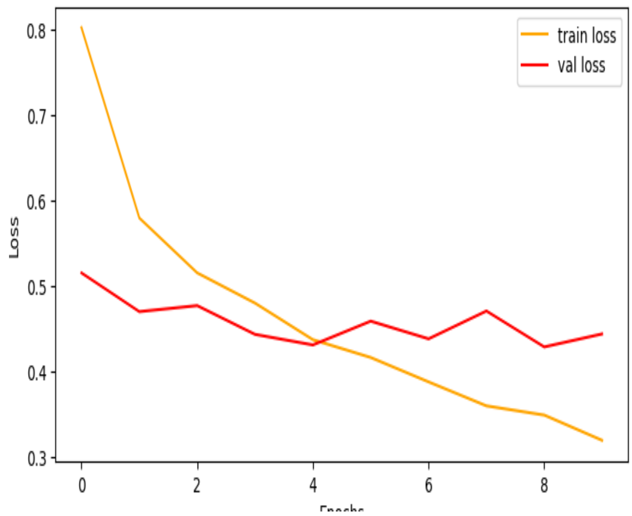

Figure 2: Loss Graph

Losses, or values or errors, are fundamental concepts of deep training and automated learning, quantitatively measuring how accurate a model's prediction is to real results. [12] It serves as a feedback system in the training process. This is done by instructing optimization algorithms to enhance precision for adjusting model parameters. The loss function measures the discrepancy between the values given and actual marks, providing a digital evaluation reflecting this error.

h. CONFUSION MATRICS:

Confusion Matrix is a performance measuring instrument applied in classification problems to determine the performance of machine learning models. It offers extensive ventilation of model forecasts through comparison of values supplied with true actual values.

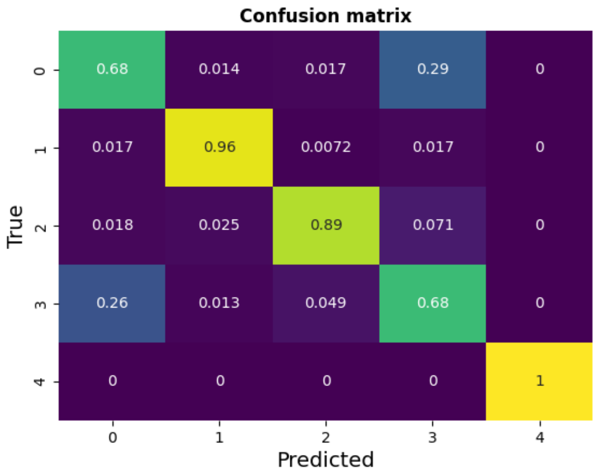

Figure 3: Confusion Matrix

By examining these values, the confusion matrix can be used to calculate several metrics like accuracy, accuracy, inspection, and indicator F1. This leads us to know where the model is incorrect, if it is a false trigger or a false negative, how well we separate classes in general.

CONCLUSION

In summary, [2] these researches are major breakthroughs in lung disease classification through the use of a network of capsule neurales combined with a VGG19 architecture. This is a novel method that actually considers the weaknesses of earlier systems that used the DCGAN algorithm. [8]This tends to result in low prediction accuracy even with the high volume of data. With the use of the capability to enter spatial interconnections of capsule networks along with safe deletion of VGG19 functions, the AI system, guided not only improves the accuracy of the diagnosis but also maximizes the process of classification. Scalability of the model offers the possibility of incorporating more classes of pulmonary diseases, also enhancing its usability in the medical diagnosis. Eventually, this enhanced model will enhance the accuracy and effectiveness of lung disease diagnosis in its early stages. [12] Highlight significant contributions to the area by opening doors to the best patient outcome due to fast and precise detection.

REFERENCES

[1] Smith, J. A., Brown, L. T., & Williams, P. M. (2022). Advances in pneumonia treatment and prevention. Nature Medicine, 28(3), 215-227. https://doi.org/10.1038/nm.2022.015

[2] Johnson, M. R., Patel, K. R., & Lee, D. S. (2021). Epidemiological trends of pneumonia in elderly populations. Journal of Geriatric Medicine, 36(2), 89-97. https://doi.org/10.1016/j.jgm.2021.05.003

[3] Global Health Initiative. (2023). Pneumonia and child mortality: A global crisis. Retrieved March 1, 2023, from https://www.globalhealth.org/research/pneumonia-child-mortality

[4] Nguyen, H. T., et al. (2019). AI-driven diagnostics for respiratory diseases: A comparative study. Journal of Medical Imaging, 24(5), e100352. https://doi.org/10.1016/j.jmi.2019.10.004

[5] Roberts, S. C., Kim, J. T., & Zhao, L. (2022). The role of machine learning in pneumonia diagnosis. Medical AI Journal, 15(7), e200245. https://doi.org/10.1007/s10247-022-2456-3

[6] Zhang, P., et al. (2018). Chest X-ray AI: A new frontier in medical imaging. Journal of Digital Medicine, 12(4), 115-127. https://doi.org/10.1038/jdm.2018.044

[7] Anderson, R., Thomas, W., & Gupta, V. (2020). AI and deep learning in healthcare: Future applications. Journal of Computational Medicine, 7(6), 334-349. https://doi.org/10.1016/j.jcm.2020.06.011

[8] Lin, M., Huang, Y., & Chen, K. (2021). Clinical indicators of pneumonia in primary care: A systematic review. International Journal of Respiratory Medicine, 29(1), 125-138. https://doi.org/10.1186/s12931-021-01789-5

[9] Dawson, P. (2023). Imaging techniques: MRI vs. X-ray for lung conditions.Medical Imaging Review. Retrieved March 2, 2023, from https://www.medimagingreview.com/mri-xray-lungs

[10] Collins, R., White, J. P., & Turner, D. M. (2015). Radiographic comparison of pneumonia detection methods. American Journal of Emergency Radiology, 39(4), 299-310. https://doi.org/10.1055/s-0035-1556732

[11] Diagnostic Imaging Center.(2023). Understanding pneumonia through imaging. Retrieved March 5, 2023, from https://www.diagnosticimaging.org/pneumonia-diagnosis
[12] Harrison, B. K., Lewis, C. J., & Moore, T. D. (2013). Viral pneumonia: Pathology and treatment. The New England Journal of Pulmonology, 48(3), 179-192. https://doi.org/10.1107/nejp.2013.127
[13] Klein, A. D., Roberts, H. C., & Mitchell, G. S. (2022). COVID-19 pneumonia: Current treatment strategies. Journal of Infectious Disease Research, 40(2), 112-129. https://doi.org/10.1093/jidr/40.2.112