International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

# Detection of Pulmonary Diseases in Lung Using CT & X-Ray Images by CNN

**Asan Nainar M[1], Praveen Kumar A[2], Sam Ruban D[3], Rahul Raj K[4], Ranjith S[5]**

[2,3,4,5]Student, Department of Information Technology, SRM Valliammai Engineering College, Chengalpattu, Tamil Nadu, India
[1]Assistant Professor-Sel.G, Department of Information Technology, SRM Valliammai Engineering College, Chengalpattu, Tamil Nadu, India

**Abstract**
Our project presents a novel approach for the automated detection of pulmonary diseases, particularly focusing on COVID-19 and effusion, utilizing Convolutional Neural Network (CNN) technology applied to CT & X-RAY images. Traditional methods often require manual interpretation, leading to delays and potential inaccuracies. Our proposed CNN-based approach offers a solution by leveraging the power of deep learning to automatically analyse CT scans & X-RAY for the presence of pulmonary abnormalities. The CNN model is trained on a diverse dataset encompassing a wide range of pulmonary conditions, including COVID-19 infections and effusion cases. The proposed system holds significant promise for aiding healthcare professionals in expedited diagnosis and treatment planning, particularly in the context of the current COVID-19 pandemic and beyond.

**Keywords**: Covid-19, Effusion, CT image, X-ray image, CNN.

## 1. Introduction

The power of Convolutional Neural Network (CNN) technology, this project aims to revolutionize pulmonary disease detection on CT images. With The Recent Global Outbreak Of Covid-19, The Need For Accurate And Efficient Diagnostic methods has become more Critical than ever. CNN models trained on large datasets can achieve high levels of accuracy in detecting pulmonary abnormalities. Once trained, CNN models can analyze a vast number of CT scans rapidly and efficiently, this scalability is particularly advantageous in healthcare settings with high patient volumes where timely diagnosis is essential. By this technology improvement , Researchers can leverage this information to develop better treatment strategies, predict disease outcomes, and contribute to the scientific understanding of pulmonary diseases.COVID-19 pneumonia and effusion on CT images offers numerous advantages, ranging from improved diagnostic accuracy and efficiency.

## 2. Related Work

The swift transmission of COVID-19 has elevated it to a public health emergency. The emergence of pneumonia stands out as a pivotal indicator for diagnosis, monitoring, and therapeutic assessment. A growing body of literature delves into imaging manifestations and associated research, shedding light on the evolving understanding of COVID-19. This review aims to provide insights into the progress and future prospects of COVID-19 imaging. It concentrates on elucidating CT findings, articulating potential pathological foundations, addressing challenges posed by patients with underlying conditions, distinguishing from other diseases, and outlining directions for future research and clinical exploration. This comprehensive overview is intended to assist radiologists in both clinical practice and research endeavors.

Automated lung cancer diagnosis from computed tomography scans involves a dual process: identifying suspicious lesions (pulmonary nodules) and evaluating overall lung/pulmonary malignancy. While numerous studies focus on the initial step, there is a notable gap in research concerning the subsequent evaluation. Given that the mere presence of a nodule does not definitively indicate cancer, and the relationship between nodule morphology and cancer is intricate, an accurate lung cancer diagnosis necessitates meticulous examination of each suspicious nodule and the integration of information from all modules.

The global outbreak of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-COV-2) has led to over 2.5 million cases of Corona Virus Disease (COVID-19), a number that continues to rise. In an effort to control the spread of the disease While pathogenic laboratory testing remains the gold standard, it is time-consuming and often yields significant false negative results. Hence, there is an urgent need for alternative diagnostic methods to effectively combat the disease. Building upon the radiographical changes observed in CT images of COVID-19, we propose that deep learning methods in Artificial Intelligence may extract specific graphical features indicative of COVID-19.

## 3. Proposed Work

In our approach to detecting lung diseases, particularly COVID-19 and Effusion, we opted for the Convolutional Neural Network (CNN) algorithm over traditional Shallow Learning Networks. By leveraging CT images, we aim to identify and differentiate between COVID-19 and Effusion. The utilization of CNN enables us to harness the power of deep learning, providing several advantages for effective disease detection. One notable strength lies in the algorithm's ability to handle large datasets, allowing for comprehensive analysis of diverse cases. Moreover, the CNN eliminates the need for human recognition, offering a more efficient and automated diagnostic process. Its high accuracy in image recognition and classification enhances the precision of disease identification. An additional benefit is the CNN's capacity to apply the same knowledge across all image locations, ensuring consistency in its diagnostic capabilities. This advanced algorithmic approach holds promise in revolutionizing the detection and classification of lung diseases, contributing to more effective and timely medical interventions.

### 3.1 Data Collection

Gather a diverse dataset of chest CT images, including both healthy and diseased cases. Ensure the dataset covers various pulmonary diseases and conditions Identify and select a diverse and representative dataset of CT images that includes cases of pulmonary diseases such as COVID-19 and Effusion. The dataset should encompass various conditions, ensuring a comprehensive training ground for the CNN.

### 3.2 Dataset Acquisition

The dataset is designed to cover a diverse range of pulmonary conditions, allowing for a thorough exploration of imaging patterns associated with COVID-19, as well as those specific to pleural effusion. Each CT scan in the dataset is meticulously selected to ensure accurate representation of the respective conditions, providing a robust foundation for training and validating machine learning models, particularly leveraging CNN technology.

**3.3 Data Preprocessing**

As part of the pre-processing pipeline for our CNN-based model, the collected images undergo several crucial steps. Initially, we resize all images to a consistent size, ensuring uniformity and compatibility for input into the CNN model. Subsequently, we normalize the pixel values across the entire dataset, scaling them to a standardized range, typically [0, 1]. This normalization facilitates model training by preventing numerical instability and promoting convergence during optimization. Additionally, to enhance the model's robustness and generalization capabilities, we employ optional data augmentation techniques. These may include rotations, flips, and zooming, introducing variability to the dataset and enabling the model to learn from a more diverse set of representations. Through these pre-processing steps, we aim to prepare a well-structured and optimized dataset for training our CNN model, ultimately enhancing its accuracy and effectiveness in detecting pulmonary diseases from CT images.

**3.4 Model Building**

The dataset is systematically divided into three subsets: training, validation, and test sets, ensuring a robust evaluation of the CNN model's performance. The training set, comprising chest CT images and their corresponding labels indicating health or disease, becomes the foundation for training the model. During this training phase, the CNN learns to discern relevant features within the images and makes associations with the provided labels.To assess the model's generalization capabilities, we validate its performance on the dedicated validation set. Metrics like loss and accuracy are closely monitored during validation, offering insights into the model's behavior and potential areas for improvement. This iterative process allows for fine-tuning hyperparameters, such as learning rate, batch size, and dropout rate, with the goal of optimizing the model's overall performance.Through this comprehensive training and validation cycle, we aim to develop a CNN model that exhibits high accuracy, sensitivity, and specificity in detecting pulmonary diseases from chest CT images. The strategic use of training, validation, and test sets, along with careful hyperparameter tuning, contributes to the robustness and effectiveness of our CNN-based diagnostic tool.

**3.5 Training**

The dataset is systematically divided into three subsets: training, validation, and test sets, ensuring a robust evaluation of the CNN model's performance. The training set, comprising chest CT images and their corresponding labels indicating health or disease, becomes the foundation for training the model. During this training phase, the CNN learns to discern relevant features within the images and makes associations with the provided labels.To assess the model's generalization capabilities, we validate its performance on the dedicated validation set. Metrics like loss and accuracy are closely monitored during validation, offering insights into the model's behavior and potential areas for improvement. This iterative process allows for fine-tuning hyperparameters, such as learning rate, batch size, and dropout rate, with the goal of optimizing the model's overall performance.Through this comprehensive training and validation cycle, we aim to develop a CNN model that exhibits high accuracy, sensitivity, and specificity in detecting pulmonary diseases from chest CT images. The strategic use of training, validation, and test sets, along with careful hyperparameter tuning, contributes to the robustness and effectiveness of our CNN-based diagnostic tool.

**3.6 Deployment**

Upon successful training and evaluation, the trained CNN model is transitioned into a practical and user-friendly application for seamless integration into healthcare systems. The development involves creating an interface that allows users, such as medical professionals or diagnosticians, to input chest CT images easily. The system is designed to leverage the trained model for swift and accurate predictions concerning the presence of pulmonary diseases.Ensuring a user-friendly experience, the interface provides a straightforward mechanism for uploading CT images, and the model processes the input promptly, delivering real-time predictions. This emphasis on efficiency facilitates prompt diagnosis and decision-making in a clinical setting. The deployment of the CNN model into such an application enhances its accessibility and usability, making it a valuable tool for healthcare professionals in diagnosing and managing pulmonary diseases using chest CT images.

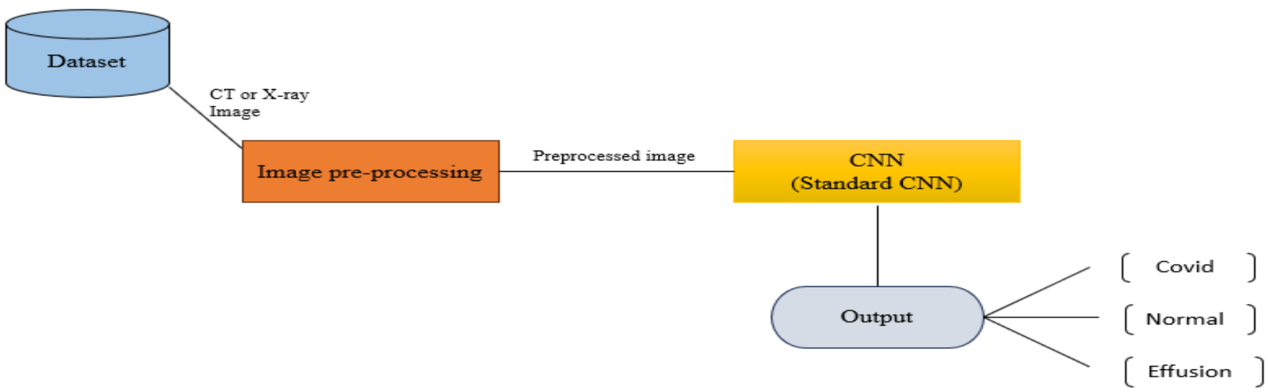
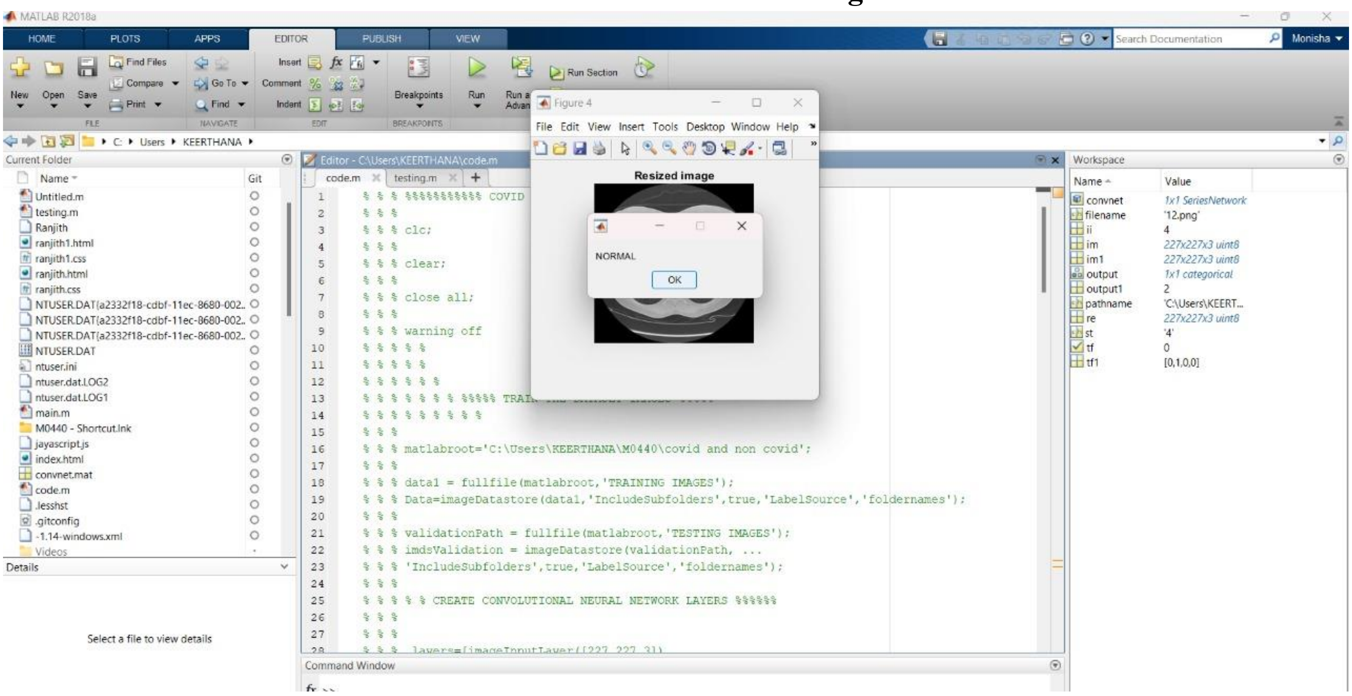


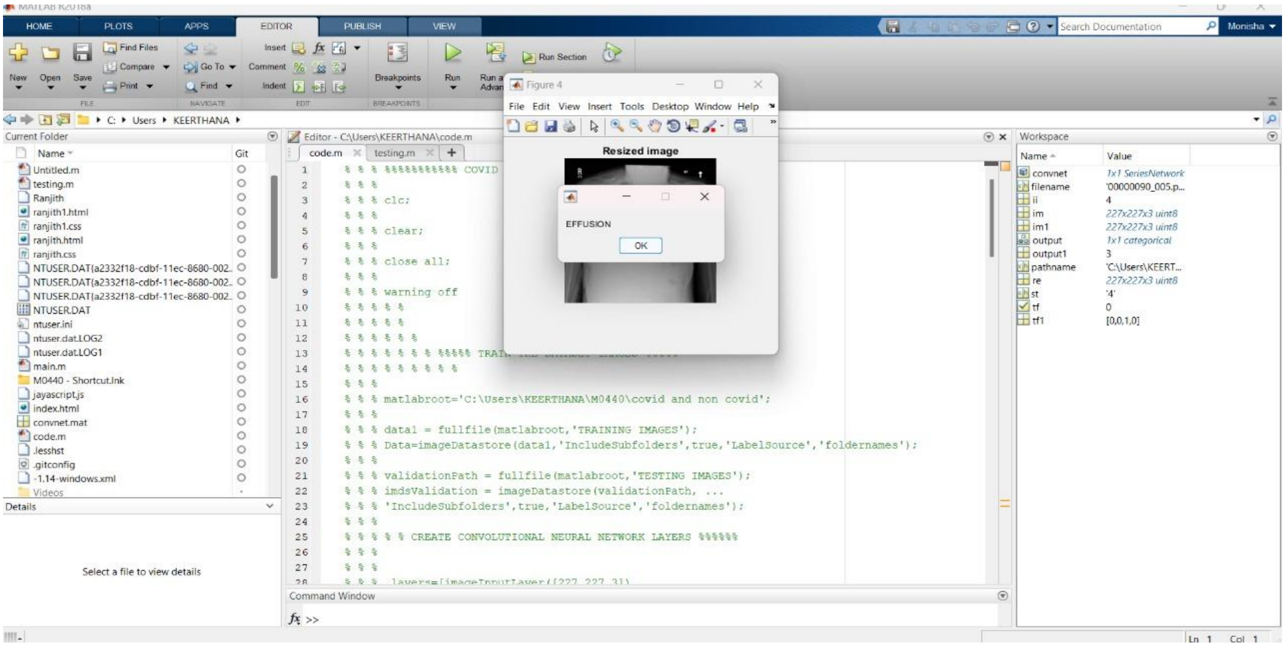

**Figure 1: System Architecture**

## 4. Results and Discussion

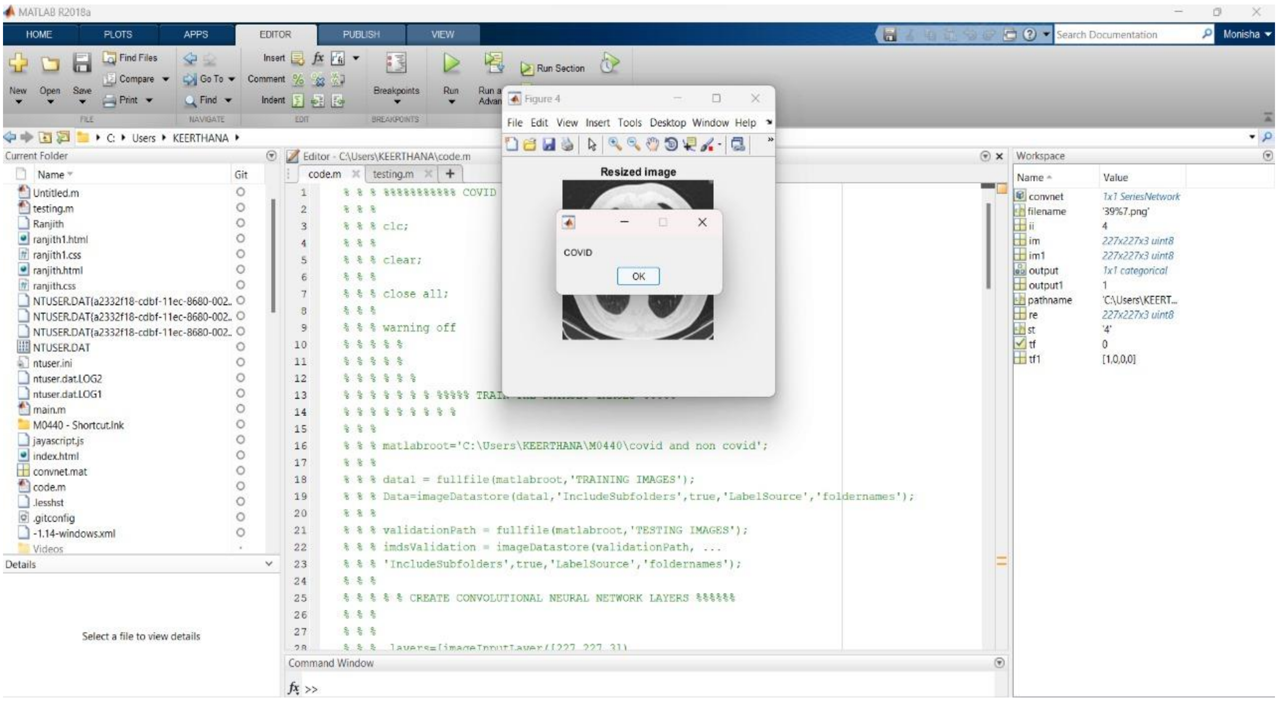
### 4.1 Result For Normal lung



### 4.2 Result For Effusion




### 4.3 Result for Covid




## Conclusion

In conclusion, our approach to detecting lung diseases, with a specific focus on COVID-19 and Effusion, leverages the Convolutional Neural Network (CNN) algorithm as a powerful tool for image analysis. The decision to employ CNNs over traditional Shallow Learning Networks is driven by the inherent strengths of deep learning, particularly in handling large datasets and achieving accurate disease detection. By training on a diverse range of cases through CT images, the CNN allows for a comprehensive analysis, offering a more nuanced understanding of pulmonary conditions.One of the notable advantages of the CNN lies in its capability to manage extensive datasets, facilitating a thorough examination of diverse cases and contributing to robust diagnostic capabilities. The elimination of the need for human recognition enhances efficiency, paving the way for an automated diagnostic process. The high accuracy of the CNN in image recognition and classification further refines disease identification, promoting precision in diagnosis.Moreover, the CNN's ability to apply consistent knowledge across all image locations ensures reliability and uniformity in diagnostic outcomes. This advanced algorithmic approach holds substantial promise in revolutionizing the detection and classification of lung diseases, marking a significant stride toward more effective and timely medical interventions. As we continue to explore the potential of CNNs in medical imaging, the integration of such technologies stands poised to significantly impact the landscape of pulmonary disease diagnosis and patient care.

**References**

1. D. Singh, V. Kumar, Vaishali, and M. Kaur, “Classification of COVID-19 patients from chest CT images using multi-objective differential evolution– based convolutional neural networks,” Eur. J. Clin. Microbiol. Infect. Dis., vol. 39, pp. 1379–1389, Jul. 2020.
2. H. Kang, L. Xia, F. Yan, Z. Wan, F. Shi, H. Yuan, H. Jiang, D. Wu, H. Sui, C. Zhang, and D. Shen, “Diagnosis of coronavirus disease 2019 (COVID-19) with structured latent multi-view representation learning,” IEEE Trans. Med. Imag., vol. 39, no. 8, pp. 2606–2614, Aug. 2020
3. S. Wang, B. Kang, J. Ma, X. Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. Li, X. Meng, and B. Xu, “A deep learning algorithm using CT images to screen for corona virus disease (COVID-19),” MedRxiv, Apr. 2020,
4. L. J. Zhen, X. G. He, and D. S. Huang, “Super-linearly convergent BP learning algorithm for feed forward neural networks,” J. Softw., vol. 11, no. 8, pp. 1094–1096, 2000.
5. M. H. Gail and S. B. Green, “Critical values for the one-sided two-sample Kolmogorov-Smirnov statistic,” J. Amer. Stat. Assoc., vol. 71, no. 355, pp. 757–760, Sep. 1976
6. T. Fernando, H. Ghaemmaghami, S. Denman, S. Sridharan, N. Hussain, and C. Fookes, “Heart sound segmentation using bidirectional LSTMs with attention,” IEEE J. Biomed. Health Inform., vol. 24, no. 6, pp. 1601–1609, Jun. 2020,
7. R. Guerrero, C. Qin, O. Oktay, C. Bowles, L. Chen, R. Joules, R. Wolz, M. C. Valdés-Hernández, D. A. Dickie, J. Wardlaw, and D. Rueckert, “White matter hyperintensity and stroke lesion segmentation and differentiation using convolutional neural networks,” NeuroImage, Clin., vol. 17, pp. 918–934, Dec. 2017
8. E. Soares, P. Angelov, S. Biaso, M. H. Froes, and D. K. Abe, “SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification,” MedRxiv, May 2020,.
9. C. Kervrann and J. Boulanger, “Unsupervised patch-based image regularization and representation,” in Proc. Eur. Conf. Comp. Vis. (ECCV), vol. 3954, 2006, pp. 555–567,
10. A. Sharma, X. Liu, X. Yang, and D. Shi, “A patch-based convolutional neural network for remote sensing image classification,” Neural Netw., vol. 95, pp. 19–28, Nov. 2017