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# Integrating Spatial and Sequential Analysis for Lung Cancer Detection

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**Abstract**

Lung cancer is still one of the most common causes of death globally, and thus early diagnosis is critical to enhance survival. The conventional diagnostic procedures usually identify lung cancer at a late stage, making early detection important. This paper presents a deep learning-based model that combines MobileNet for efficient feature extraction and LSTM for analyzing sequential patterns to enhance early lung cancer detection. MobileNet effectively captures key medical image features, while LSTM identifies temporal dependencies, improving diagnostic accuracy. The model's lightweight architecture allows for real-time deployment, making it particularly useful for mobile-based diagnostics and low-resource settings. With its high accuracy, this AI-powered solution holds great potential for clinical decision-making, early intervention, and cost-effective diagnosis.

**Keywords:** Long Short-Term Memory (LSTM), MobileNet, deep learning, feature extraction.

## 1. Introduction

Detecting lung cancer at an early stage is crucial as it can significantly impact a person's health and survival [1]. However, early detection remains a challenging task, making it difficult to diagnose the disease before it progresses [2]. One of the main reasons for lung cancer is the use of tobacco, which is responsible for almost 90% of cases [3]. Smoking and prolonged exposure to tobacco products greatly increase the risk of developing this life-threatening disease. Lung cancer is also one of the leading causes of death worldwide. According to the World Health Organization (WHO), in 2018 alone, the disease claimed 1.76 million lives, contributing to a total of 9.6 million deaths globally. These alarming numbers highlight the urgent need for better screening methods, awareness, and early intervention to improve survival rates. Lung cancer affects an average of 22,475 men and 8,390 women annually in Indonesia, where the percentage of cancer-related deaths for males is 21.8% and for women it is 9.1%, according to WHO figures (WHO, 2018).

Conventional diagnostic methods, like chest X-rays and CT scans, depend largely on the skills and experience of radiologists. While these techniques are widely used, they can be time-consuming and may sometimes lead to human errors in interpretation. Additionally, early-stage lung cancer is often difficult to detect using conventional methods, leading to delayed treatment and reduced chances of recovery [4].

This paper introduces a hybrid deep learning model, specifically combining MobileNet, a light-weight CNN with LSTM networks for the purpose of detection of lung cancer at early stage. MobileNet is tasked to extract the feature from medical images, such as CT scans while LSTM networks further analyze sequential patterns in the features extracted for further improvement in accuracy. Therefore, this approach may be able to identify early cancerous patterns where the conventional systems might miss and also because it is lightweight for MobileNet so that the overall system can really work in the real-time platform and can make the system well suited for use in mobile-based diagnostic tools.

## 2. Literature work

Lung cancer is the most challenging disease to diagnose at an early stage since the primary symptoms for this disease are extremely weak and negligible, and therefore are the traditional methods of diagnosis. With recent advancements in deep learning and artificial intelligence, new techniques have been introduced to help in early detection with increased levels of accuracy in classifications. Raza et al. [5] presented a framework based on deep learning using CNNs that helps detect lung cancer from medical images. Their study proved to significantly improve classification performance through automatic extraction of key features from X-ray and CT images, thereby reducing dependence on manual interpretation by radiologists. The findings are indicative of the potential that CNNs may bring to improve diagnostic precision in resource-constrained environments where expert radiologists are not always available.

Liu et al. [6] advanced the research further by creating a hybrid deep learning model that integrated CNNs with Long Short-Term Memory (LSTM) networks. The hybrid model allowed for sequential analysis of images, which would help the model to detect patterns over multiple frames of medical scans. The study showed that including temporal dependencies in feature extraction improved early-stage lung cancer detection significantly. Similarly, Singh et al. [7] developed an AI-based system to classify lung cancer with the use of X-ray imaging applied toward early-stage tumor detection. They applied their system based on the machine learning techniques for streamlining and automating various diagnostic processes and minimizing the reliance on expertise-based diagnosis and decreasing false positives. In an attempt to create light and efficient deep learning models, the researchers [8] formulated a lung cancer detection system by using MobileNet and the LSTM networks. Kumar et al. optimized a model for mobile-based applications so that people in distant or underdeveloped regions could access such products and services. MobileNet's characteristics of being lightweight, accompanied with LSTM as analysis sequences, were found to provide a highly accurate yet computationally efficient solution for lung cancer screening. Chen et al. [9] further explored a hybrid deep learning approach that combined traditional feature extraction methods along with deep learning classifiers to distinguish high-accuracy between malignant and benign lung nodules. Their research demonstrated the efficient use of handcrafted and deep learning-based features for enhanced reliability in diagnosis.

Expanding further on this, Xu et al. [10] proposed a MobileNet-LSTM framework for early-stage lung cancer detection that enabled efficient and accurate performance. Their model took advantage of the ability to process large-scale medical image datasets and achieved low computational costs. The success of such AI-based models highlights the increasing applications of deep learning in medical diagnostics, especially in lung cancer detection. A collective result of these studies puts across the point that CNNs, LSTMs, and hybrid AI approaches can enhance early detection, reduce human errors, and enable timely medical intervention in lung cancer patients. Continuing changes in research, deep learning-based lung cancer detection systems promise to revolutionize clinical diagnostics and offer scalable and accessible solutions to combat one of the world's deadliest diseases.

## 3. Existing System

Classic screening tests for lung cancer employ imaging methodologies, like X-rays and CT scans, and the results are interpreted by a radiologist to identify abnormalities. Although X-rays are the most frequently used for preliminary screening, they tend to fail in early detection, especially when the tumor is small and located in hard-to-visualize areas. This will involve manual interpretation of CT scans, which consumes a lot of time and also introduces human errors that may cause misdiagnosis or failure to detect early-stage tumors. It usually results in false positives and false negatives when using conventional methods, leading to unnecessary medical procedures or delayed treatment. Additionally, such approaches require vast resources and therefore are impractical for low-resource healthcare settings, making them not ideal for real-time diagnosis. Consequently, the effectiveness of early and accurate detection of lung cancer is greatly hindered.

**Disadvantages:**

1. Difficulty in detecting small or hidden tumors often leads to late stagediagnoses, limiting treatment effectiveness.
2. High costs and the need for skilled professionals limit feasibility in underdeveloped regions.

## 4. Proposed Methodology

The system reduces the limitations of the traditionally used diagnostic systems by using a hybrid approach based on MobileNet, CNN, and LSTM networks. Such an approach combining multiple architectures of deep learning increases the precision and efficiency rate of lung cancer detection. The use of advanced machine learning techniques helps detect early cancerous growths that are hard to be diagnosed using conventional approaches. MobileNet is a critical module in the system that extracts fundamental features from images, such as CT scans and X-rays. It has been selected because of its ability to preserve the quality of feature extraction while drastically lowering the computational complexity. This renders the model to be efficient, and suitable for real-time applications, with fast image processing being both accurate and fast without any need for great computational resources.

After feature extraction, the task of analyzing this data is mostly performed by an LSTM network. Since LSTM focuses more on capturing sequential patterns or relationships, the application of detecting minor abnormalities suggesting early-stage lung cancer is effective with this technology. The probability of detecting malignant growths may not be present using traditional means when the temporal dependencies in the medical images captured by the model are considered. The proposed model has been designed to be very efficient, with a lightweight architecture suitable for mobile-based diagnostic systems. It can be deployed in low resource environments, thereby making advanced lung cancer detection more readily available in remote or under-developed areas. The selection of high-quality diagnostic tools available will improve early detection rates, saving many from the dreaded disease.

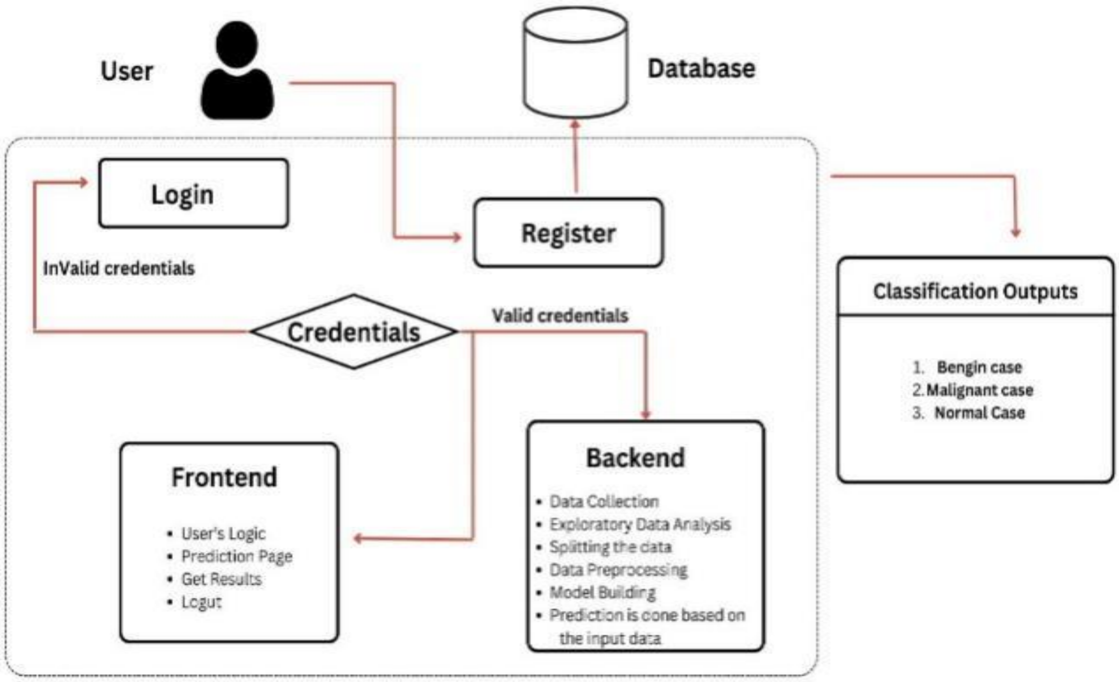


**Fig-1:** Architecture

## 1. Dataset

The Iraq-Oncology Educating Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset was obtained over three months in the autumn of 2019 from specialized cancer clinics. The dataset comprises CT scans on patients diagnosed with lung cancer at various stages, in addition to scans on healthy patients. For accuracy purposes, oncologists and radiologists at the hospitals vetted and checked the images thoroughly. Altogether, the data comprise 1,190 CT scan images for 110 cases (as illustrated in Figures 2, 3, and 4). These 110 cases belong to three different classes: Normal (55 cases), indicating subjects showing no symptom of lung cancer; Benign (15 cases), for those who are detected with non-malignant conditions in the lung; and Malignant (40 cases), for patients found to have lung cancer. The images were initially gathered in DICOM and were scanned via a Siemens SOMATOM scanner. The scan parameters consisted of 120 kV voltage, slice thickness of 1 mm, and window width between 350 and 1200 HU with window center between 50 and 600 HU to facilitate enhanced understanding of the image. All the images were de-identified in order to keep patients confidential. The research was granted approval by the institutional review board, and written consent was waived by the oversight committee. Every patient received several CT slices, with the number of slices per case varying between 80 and 200. Every slice takes a cross-sectional view of the chest from various angles, giving detailed information for medical examination. The 110 participants in the sample are from different backgrounds that differ in terms of gender, age, education level, and living conditions. Some work at Iraq's Ministry of Transport and Oil, while others are farmers or daily workers. The participants largely hail from central Iraq, that is, the Baghdad, Wasit, Diyala, Salahuddin, and Babylon provinces.

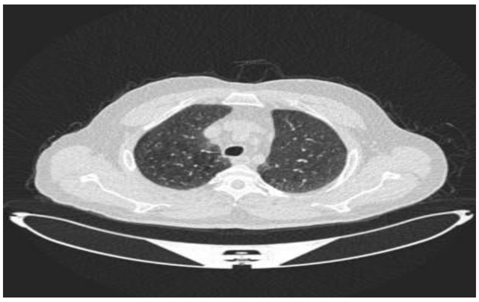

**Fig-2:** Normal

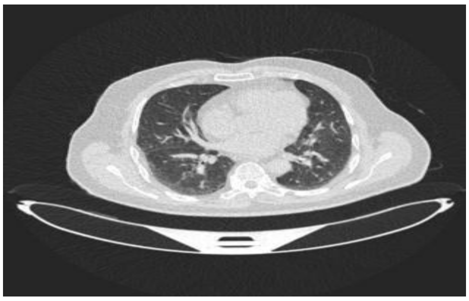

**Fig-3:** Benign

**Fig-4:** Malignant

## 2. Proposed System Flow

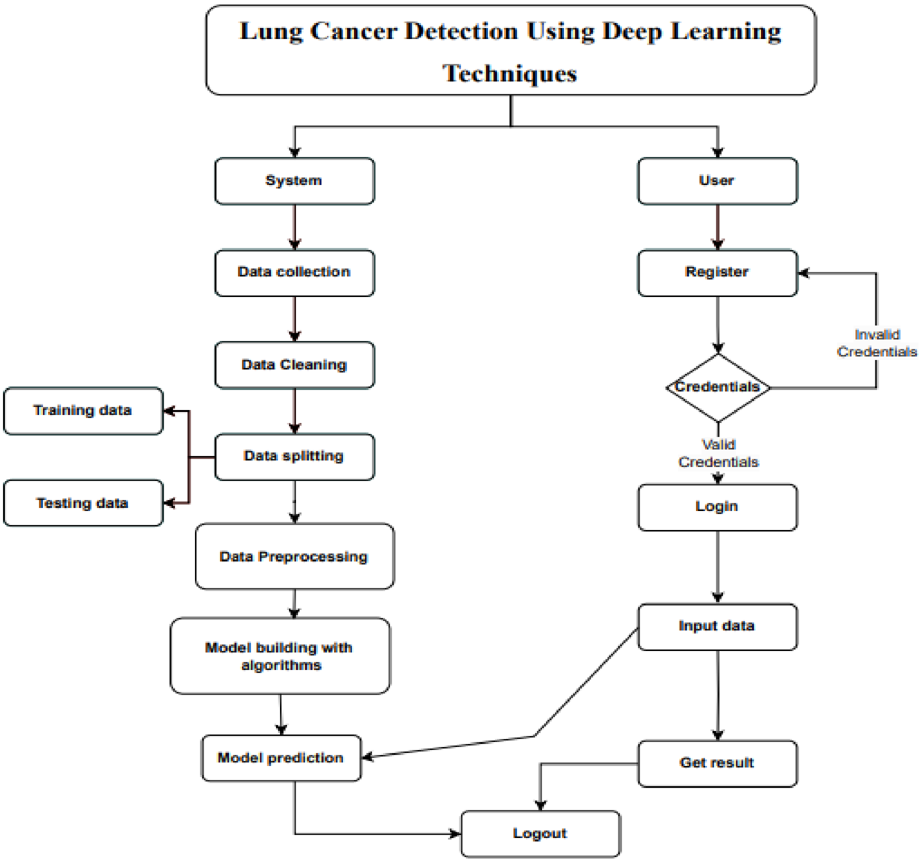


**Fig-5:** Flow Diagram

The lung cancer detection system that uses deep learning techniques consists of two main processes: system-side operations and user interactions. The process of the system starts with the collection of data which is then followed by cleanliness or data cleaning procedure to maintain the quality of the data. The cleaned data is then distributed into training and testing sets, which is the first step before going through preprocessing. The procedure is initiated by building the predictive model using machine learning algorithms, and then later the lung cancer is detected. An individual has to register and give credentials for authentication which is the first step on the user side. Only by inputting the right login information, they are granted access to their accounts and then submit their medical data to the system and receive the diagnostic results. Following that, the guarding system allows users to log out so that they can obtain their results, and, thus, ensures a safe and efficient experience.

## 3. Evaluation Metrics

A model's performance in classification tasks must be evaluated using evaluation metrics. The reliability of positive predictions is the focus of precision, whereas accuracy offers a measure of overall correctness. Particularly for unbalanced datasets, the F1-score strikes a balance between precision and recall, whereas recall guarantees that true positives are detected. The best model for a particular problem can be chosen with the use of these measures.

**Accuracy (ACC):** Calculates the total accuracy of a model by dividing the properly predicted cases (True Positives + True Negatives) by the total instances.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

**Precision (P):** Calculates the proportion of correctly predicted positive instances to the total predicted positives to aid in the quantification of false positives.

$$P = \frac{TP}{TP + FP} \quad (2)$$

**Recall (R):** Calculated by the proportion of correctly identified positive instances to the true positive instances to quantify false negatives.

$$R = \frac{TP}{TP + FN} \quad (3)$$

**F1-Score (F1):** Harmonic mean of precision and recall to balance the two metrics to generate a single performance measure, which is particularly useful in imbalanced datasets.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

## 5. Results and Discussions

The confusion matrix provides a clear comparison of how well the MobileNet-LSTM model identifies lung cancer. It visually represents the number of cases the model correctly or incorrectly classifies, showing true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) across benign, malignant, and normal categories. A higher number of correct classifications indicates the model's effectiveness in detecting lung cancer, particularly in its early stages.

The following are the confusion matrices for the proposed system.

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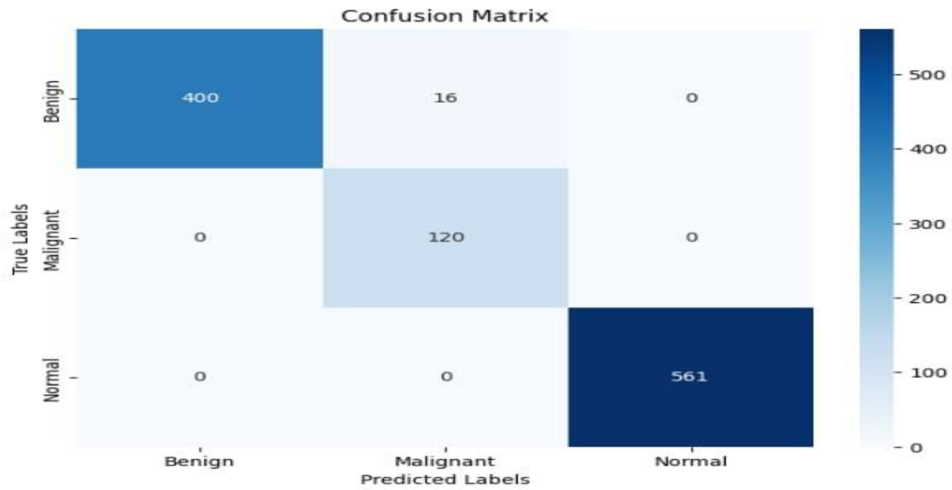


**Fig- 6:** Confusion Matrix for Benign, Malignant, Normal Cases

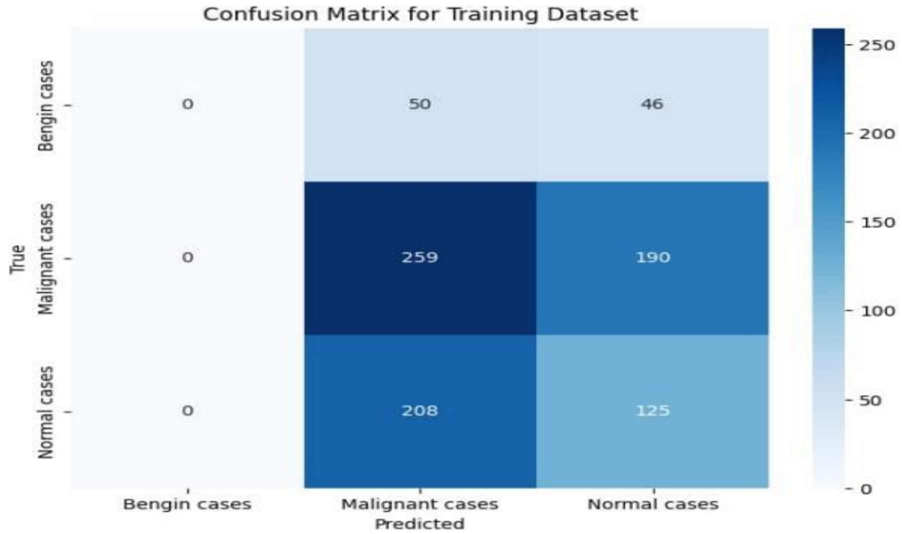


**Fig-7:** Confusion Matrix for Training Dataset

Fig 8 presents a comparison between the accuracy of the CNN model and the Hybrid Model (LSTM-MobileNet). The graph illustrates how effectively each method detects lung cancer. From the figure, it is clear that the Composite Model outperforms the CNN model, achieving higher accuracy in lung cancer detection.

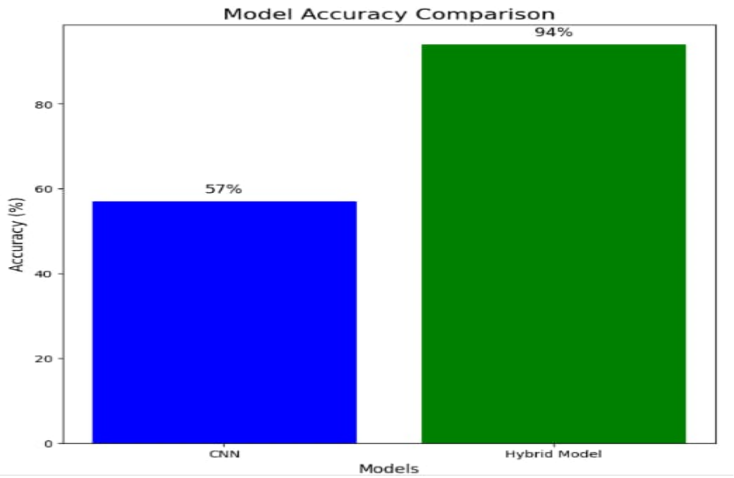


**Fig-8:** Model Accuracy Comparison

We are creating an easy-to-use website for this suggested method that will let users accurately and conveniently diagnose lung cancer and determine its stage. It will employ HTML for web page structuring, providing semantic page layout for easy navigation. CSS will be employed for styling the pages to make them look great and device-responsive. JavaScript will be responsible for handling user input and dynamic information like real-time cancer detection and stage projection based on provided data. Because of MySQL's high performance, 24/7 uptime, lower total cost of ownership, and open source flexibility, we utilize MySQL as the database in which we keep the CT scan images.

The GUI for the suggested system is shown below.

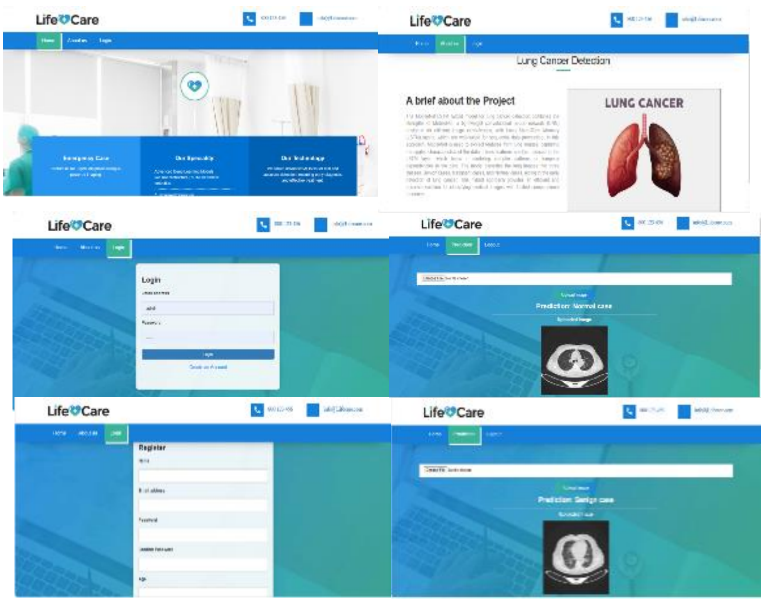


**Fig-9:** User Interfaces

## 6. Conclusion

The new hybrid MobileNet-LSTM model presents a fast, accurate solution to early diagnosis of lung cancer. Through effective utilization of the feature extraction prowess of MobileNet and sequential analysis ability of LSTM, it captures diagnostic delay, human error, and resource limits. The model presents high precision and computational saving, which qualifies it for application in real-time-based mobile diagnosis equipment and constrained resources. The model promotes effective early detection that can enable prompt intervention and improve the patient outcomes. Lightweight architecture facilitates handheld deployment, reaching more distant communities with limited medical professionals. Through automation and enhancing diagnostic precision, it supports radiologists while diminishing manual labor. This effort is a step in the direction of incorporating AI-powered deep learning in clinical use for cost-effective and efficient lung cancer diagnosis.

## 7. Future Work

Future updates to the lung cancer detection system could include integrating advanced deep learning models like ResNet or DenseNet, famous for their capability to inspect complicated patterns in medical images, potentially improving detection accuracy. Another enhancement could involve Transfer Learning, where pre-trained models from large datasets are adjusted to specific tasks, especially useful when working with limited labeled data. Refining the preprocessing pipeline by incorporating advanced image denoising techniques could enhance low-resolution or noisy scans, leading to more precise feature extraction. Additionally, contrast enhancement methods such as Histogram Equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization) could improve image clarity, making it easier to detect early-stage cancerous lesions. By combining these advancements, the system's diagnostic capabilities could be significantly improved, making it more suitable for real-world clinical use.

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