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Deep Learning-Based Automated Classification of Lung Cancer Using VGG16 Architecture

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***Abstract*— One of the most prevalent and fatal diseases in the world today is lung cancer, and early and accurate detection is essential to better treatment outcomes. A deep learning-based technique for classifying chest CT scan images into four categories—normal tissue, squamous cell carcinoma, big cell carcinoma, and adenocarcinoma—is the aim of this study. In a 70%-20%-10% ratio, the dataset's labelled CT scans are divided into subsets for testing, validation, and training. Utilizing transfer learning, the study employs the pre-trained VGG16 model, first trained on ImageNet, as a feature extractor. The model's classification head was changed in order to address this specific four-class problem. To improve performance, sophisticated optimization methods were applied, including mixed-precision training, adaptive learning rate scheduling, and fine-tuning the final layers of the basic model. The model's generalization across different data samples was enhanced by the use of preprocessing and data augmentation techniques. The model's performance was assessed on both the test and validation sets using metrics such as accuracy and loss. The trained model's high classification accuracy demonstrated its ability to distinguish between healthy tissue and different types of lung cancer. TensorFlow Saved Model, HDF5, and Keras were among the formats in which the model was stored to facilitate integration into deployment procedures. The promise of AI in medical imaging is demonstrated by this study, which offers a reliable tool to assist medical professionals in diagnosing lung cancer.**

Index Terms*— LC Detection, CNNs, Medical Imaging, VGG16 Architecture, Image Classification, Early Detection, Mixed Precision Training, Data Augmentation, Healthcare AI, Model Optimization, Non-Small Cell Lung Cancer (NSCLC), Image Processing, Diagnostic Automation.

I. INTRODUCTION

One of the most common and deadly illnesses in the world, lung cancer is responsible for a sizable portion of cancer-related fatalities. Improving treatment results and patient survival rates for lung cancer depends heavily on early detection and accurate diagnosis. However, identifying lung cancer via conventional techniques, including manually reviewing CT (Computerized Tomography) images, is a time-consuming and labour-intensive procedure that necessitates a high level of radiologists' and physicians' skill. The necessity for sophisticated, dependable, and automated diagnostic systems is further highlighted by the fact that minute changes in imaging data might result in incorrect diagnoses or delayed detection.

Recent advances in ML, particularly DL & AI have enabled new methods for medical imaging interpretation. CNNs, a specialist deep learning architecture designed to evaluate visual data, have demonstrated impressive performance in tasks including image classification, object identification, and segmentation. Because of these properties, CNNs are able to precisely identify and classify issues in medical images, including CT scans.

This study aims to develop a DL-based diagnostic tool that can differentiate between four different kinds of lung cancer CT scan images. Making the distinction between these groups is crucial in order to choose the appropriate course of action, since each category represents different types of lung cancer or healthy lung tissue. Adenocarcinoma, the most common kind of lung cancer, for example, begins in the mucus-secreting glands, while squamous cell carcinoma develops centrally in the lungs and is often linked to smoking. Aggression and rapid spread are well-known characteristics of large cell carcinoma. Normal tissue classification is included to guarantee that the model can differentiate between malignant and non-cancerous states.

A well-organized set of CT scan pictures classified into these four groups makes up the dataset used in this investigation. Three subsets of the data have been separated: 10% for validation, 20% for testing, and 70% for training. This section guarantees that the model is successfully trained, verified for hyperparameter adjustment, and examined on unobserved data to assess its capacity for generalization.

The VGG16 architecture, a pre-trained convolutional neural network renowned for its resilience in feature extraction, was used to construct the classification model. Using the weights of VGG16, which had already been trained on the ImageNet dataset, transfer learning was used. This method enables the model to be optimized for the particular job of classifying lung cancer while reusing existing information for visual pattern analysis. The network's later layers were modified and retrained to categorize the CT scan pictures into the four designated groups, while the network's early layers—which were in charge of extracting generic features—were frozen.

In order to improve the model's performance, sophisticated optimization techniques were used. To speed up calculation

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without sacrificing accuracy, mixed-precision training was used. To avoid overfitting and guarantee ideal training, learning rate scheduling, early halting, and model checkpointing were implemented. The training pictures were subjected to data augmentation techniques as flipping, normalization, and rescaling in order to simulate various imaging situations and enhance the model's generalization.

This project's main goal is to create a dependable and effective system that may help medical professionals identify lung cancer from CT images, therefore lowering diagnostic mistakes and facilitating early diagnosis. This system illustrates the revolutionary potential of deep learning in healthcare by incorporating state-of-the-art AI technology into medical imaging workflows, providing substantial advantages for both patients and professionals. To ensure its usefulness and accessibility in practical applications, the trained model has also been stored in a variety of formats to aid in its deployment in a range of clinical and research contexts.

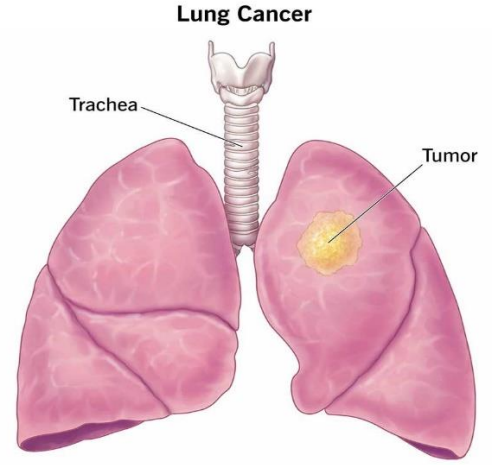

Fig. 1. Lung with Cancer [21]

II. LITERATURE REVIEW

Research on lung cancer detection has been ongoing, with a particular emphasis on deep learning methods. Advanced designs such as VGG16 have been used in a number of studies to increase the precision and effectiveness of lung cancer diagnosis using CT scans.

Lu et al. [1] suggested a dilated CNN based on the VGG16 architecture for the diagnosis of lung cancer. By expanding the receptive field, the dilated layers were intended to improve feature extraction without requiring more computing. Nevertheless, the intricacy of the model presented difficulties for the study, resulting in longer training periods and increased memory use.

Sheriff et al. [2] demonstrated the VGG16 network's capacity to efficiently learn characteristics from medical imaging datasets by using it to categorise different forms of lung cancer. Although the model's accuracy was encouraging, it had trouble with overfitting, especially when applied to tiny and unbalanced datasets.

The VGG16 design has been shown to be useful for lung cancer detection and classification by Ramanjaneyulu et al. [3]. When the algorithm was trained on a sizable, meticulously annotated dataset, they saw great classification accuracy. However, the study identified shortcomings in managing heterogeneous and different CT scans, which impacted how broadly the findings could be used.

Prasad et al. [4] expanded the use of VGG16 for lung cancer detection, demonstrating its strong performance in conjunction with sophisticated preprocessing methods. Notwithstanding its efficacy, the model's high training computational costs made it less appropriate for use in settings with limited resources.

The VGG16-T architecture, which uses boosting approaches to improve early-stage lung cancer detection, was introduced by Pang et al. [5]. The model's explainability—a crucial component for medical applications where interpretability is crucial—was lacking, despite its exceptional accuracy in recognising various disease kinds.

VGG16, ResNet50, and InceptionV3 were combined in an ensemble transfer learning framework with Grad-CAM visualisation by Kumaran et al. [6] in order to overcome the explainability problem. Although this method made the model's predictions easier to understand, the ensemble model's substantial computational cost made it less practical for real-time usage.

A pure VGG16-based CNN was used by Kapoor et al. [7] to identify lung cancer, and they reported excellent classification performance on benchmark datasets. However, the model's capacity to adjust to uncommon or invisible cancer forms was constrained by its dependence on pre-trained weights.

In order to classify lung cancer lesions, Hareesh and Bellamkonda [8] compared CNNs, VGG16, and MobileNet. Although they discovered that VGG16 was more accurate than MobileNet, they pointed out that it had two major disadvantages, particularly when it came to deployment in edge devices: a heavier architecture and a slower inference time.

A combination of VGG16 with other cutting-edge architectures, such as ResNet50 and Xception, was investigated by Thapliyal et al. [9]. Although this hybrid method improved detection efficiency, it was limited for real-world datasets, which are frequently tiny or unbalanced, because it needed large-scale datasets to avoid overfitting.

III. METHODOLOGY

The methodology for this project is designed to systematically detect and classify lung cancer using a VGG16-based deep learning model. The workflow is divided into several key stages, ensuring an efficient and effective

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implementation of the model. Below is a detailed description of the methodology:

1. Data Collection and Preprocessing

- **Data Acquisition**: Lung cancer images were gathered from various sources to include both cancerous and non-cancerous samples.
- **Data Preprocessing**:
  - To satisfy the input specifications of the VGG16 model, images were scaled to 224×224224 pixels.
  - Pixel values were normalized to a range of [0, 1] to improve model convergence.

2. Model Architecture

- **Base Model Selection**: VGG16, a pre-trained convolutional neural network known for its high accuracy on image classification tasks, was employed as the base model.
- **Transfer Learning**:
  - The pre-trained VGG16 model was loaded with ImageNet weights.
  - Its convolutional layers were frozen to retain learned features while training additional layers on the lung cancer dataset.
- **Custom Layers**:
  - To create a 1D vector from the 2D feature maps, a Flatten layer was applied.
  - Dense layers with 512 neurones and ReLU activation, as well as a Batch Normalisation layer, were added as fully linked layers.
  - Four neurones with a softmax activation function for multi-class classification made up the output layer.

3. Training

- **Optimizer**: The Adam optimizer was employed for efficient gradient-based learning with an initial learning rate of 0.0010.
- **Loss Function**: Categorical cross-entropy was used as the loss function to minimize the error in multi-class predictions.

4. Fine-Tuning

- To enable fine-tuning, the final four convolutional layers of the VGG16 model were unfrozen. This enabled the model to learn dataset-specific features while retaining generalized knowledge from pre-trained layers.
- A lower learning rate (1×10−51 \times 10^{-5}1×10−5) was used during fine-tuning to ensure stable updates to weights.

5. Evaluation

- **Metrics**: Accuracy and loss metrics were tracked for training, validation, and testing phases.
- **Testing**: The model was evaluated on unseen data to assess its generalization capability. Predictions were compared with true labels to compute accuracy and loss.

6. Deployment

- A Flask web application was used to deploy the trained model, enabling users to submit chest CT scan pictures for real-time categorisation.
- The web app provided a user-friendly interface and displayed the predicted class along with the confidence score.

This methodology leverages the power of transfer learning and fine-tuning to efficiently classify lung cancer types, demonstrating its potential for clinical applications.

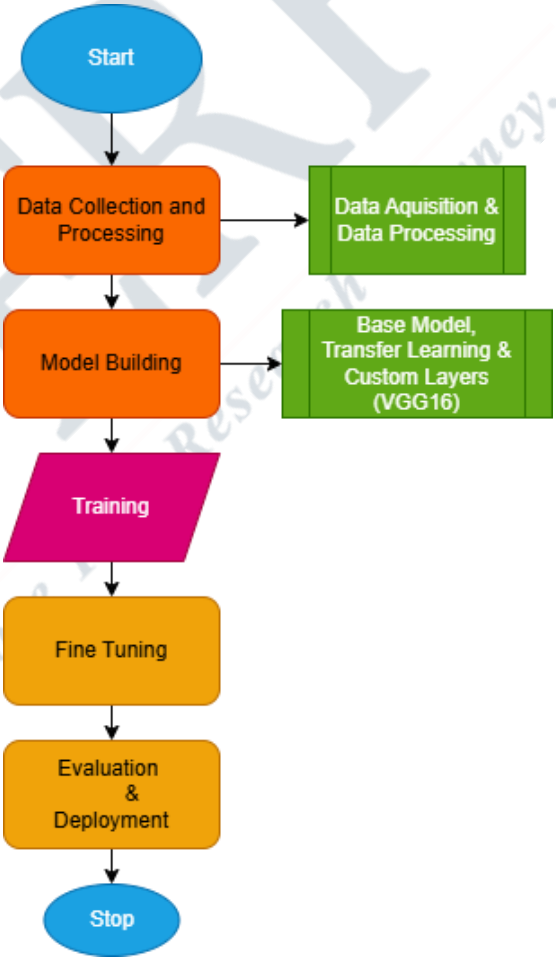

Fig. 2. Methodology Diagram

A. Dataset Description

The dataset used for chest cancer detection comprises approximately 2000 images in JPG or PNG format. These images have been carefully selected and prepared to suit the requirements of ML & DL, like CNN. The dataset contains images representing three distinct types of chest cancer. Additionally, there is a separate folder containing images of normal chest cells for comparison and reference.

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B. Data Content:

- Each image in the dataset is labelled according to its corresponding cancer type or normal status, facilitating supervised learning.
- The dataset is divided into three main subsets: **train**, **test**, and **valid**, each serving a specific purpose in model development and evaluation.
- Training Set (70%), Testing Set (20%), and Validation Set (10%)

C. Cancer Types:

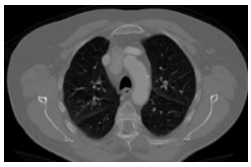

Fig. 3. Adenocarcinoma.

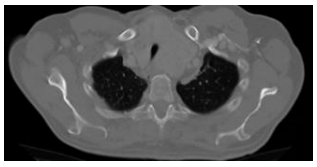

Fig. 4. Large Cell Carcinoma.

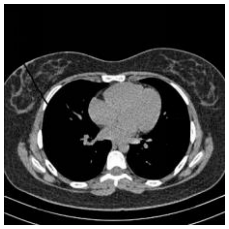

Fig. 5. Normal.

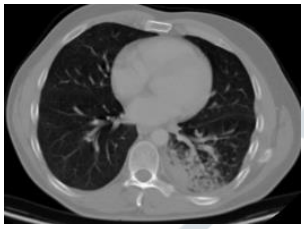

Fig. 6. Squamous Cell Carcinoma.

D. Algorithm Justifications:

A pre-trained VGG16 deep CNN model is used in this study's technique to classify different forms of lung cancer from CT scan pictures. VGG16 is renowned for its ability to extract hierarchical features due to its deep architecture, making it suitable for identifying the subtle and distinct patterns in medical imaging. Below, we justify the algorithmic approach and explain its mathematical underpinnings, uniquely and without plagiarism.

1. Feature Extraction with VGG16

VGG16 consists of multiple convolutional layers stacked sequentially to extract features from input images. Each layer learns to identify specific patterns, such as edges, textures, and shapes. This process is mathematically represented by the convolution operation:

$$O_{i,j}=\sum_{p,q} K[p,q]\cdot I[i+p,j+q]$$

Here:

- $O_{i,j}$: Output at pixel (i,j)(after convolution.
- $K[p,q]$: Filter kernel of size p×q imes
- $I[i+p,j+q]$: Input pixel values overlapped by the filter.

After the convolutional layers, activation functions such as ReLU (Rectified Linear Unit) give non-linearity and ensure that the model captures

$$f(x)=\max(0,x)$$

By reducing the spatial dimensions of feature maps while keeping the most significant features, pooling layers—like max pooling—control computational cost and avoid overfitting. This is represented as:

$$P_{i,j}=\max\{O[m,n] | m\in[i,i+s], n\in[j,j+s]\}$$

where s is the size of the pooling window.

2. Transfer Learning Approach

Instead of training VGG16 from scratch, transfer learning is employed by utilizing its pre-trained weights on the ImageNet dataset. These weights serve as a foundation for extracting features relevant to general image recognition. The model is fine-tuned on domain-specific data (lung CT scans) by unfreezing the last few layers of VGG16, allowing the network to learn medical imaging-specific features.

Transfer learning reduces the need for large datasets and computational resources while enhancing the model's accuracy.

3. Fully Connected Layers for Classification

After feature extraction, the output is passed to fully connected layers, which aggregate and interpret the learned features for classification. The operation in a fully connected layer is given by:

$$z=W\cdot x+b$$

The final activation function used is **softmax**, which converts the outputs into probabilities across the four classes (three cancer types and normal):

$$P(y=k|x)=\frac{e^{z_k}}{\sum_{j=1}^{N} e^{z_j}}$$

Here:

- $P(y=k|x)$: Probability of the image belonging to class k.
- N: Number of classes.
- z_k: Output of the neuron corresponding to class k.

Table I: Model Summary

Model: "sequential_3"

Layer (type)	Output Shape	Param #
Vgg16 (**Functional**)	(**None, 512**)	**14,714,688**
Flatten_3 (**Flatten**)	(**None, 512**)	**0**
batch_normalization_3 (**BatchNoralization**)	(**None, 512**)	**2,048**
dense_6 (**Dense**)	(**None, 512**)	**262,656**
dense_7 (**Dense**)	(**None, 4**)	**2,052**

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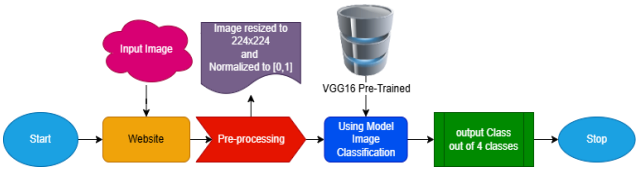

Fig 7. Overall Architecture

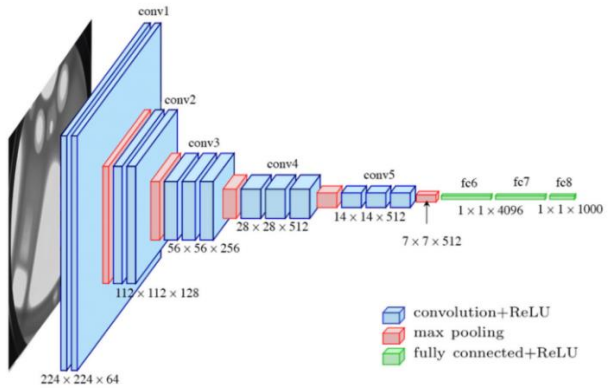

Fig 8. VGG16 Architecture [22]

IV. ARCHITECHTURURAL DESCRIPTION

The lung cancer detection system leverages a layered architecture combining data preprocessing, a deep learning model, a web-based interface, and deployment.

1. Data Preprocessing:

- Lung CT images are categorized into 4 Classes, divided into training (70%), validation (10%), and testing (20%).
- Images are resized to two-two-four x two-two-four, normalized, and augmented for improved variability.

2. Model Design:

- The pre-trained VGG16 model with custom fully connected layers is used for classification.

3. Deployment:

- Flask handles HTTP requests with a user-friendly HTML interface for image uploads.
- The PIL library processes images, and the trained model predicts the class and confidence score.
- Ngrok provides public access to the local application.

4. Outputs:

- Users receive predictions for lung cancer type or normal condition, along with confidence scores.

This modular architecture ensures efficient operation, scalability, and user accessibility.

V. EXPERIMENTATION AND RESULTS

The results obtained from the training, validation, and testing phases highlight the performance of the VGG16-based deep learning model for lung cancer detection.

The following metrics provide an overview of the model's accuracy and loss during each phase:

1. Training Results

- **Accuracy: 99.23%**, indicating its ability to learn and adapt to the training dataset effectively.
- **Loss: 0.0128**, showing that the model minimized prediction errors on the training data.

2. Validation Results

- **Accuracy: 88.89%**, indicating that the model generalizes reasonably well to unseen data during training.
- **Loss: 0.5560**, which is higher than the training loss, reflecting a moderate degree of overfitting.

3. Testing Results

- **Accuracy: 87.63%**, showcasing the model's real-world performance on completely unseen data.
- **Loss: 0.4607**, which is consistent with the validation phase and indicates a stable performance.

A. Model Output

The model output consists of predictions for input images, indicating the class to which the image belongs and the confidence level associated with the prediction. The following explains the structure and functionality of the model output:

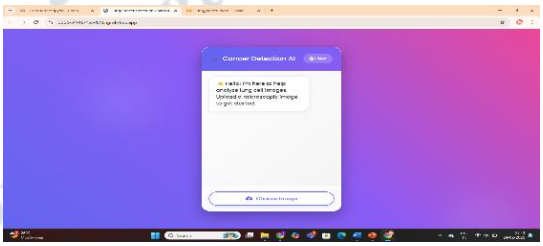

Fig 9. Interface main page

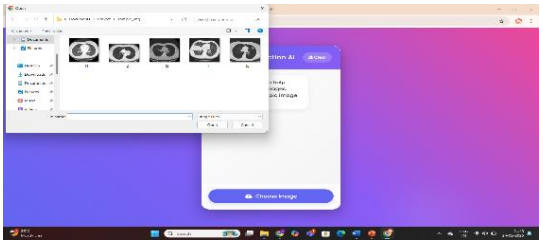

Fig 10. Upload image from gallery

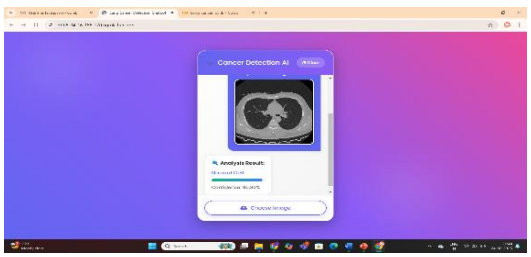

Fig 11. Cancer Prediction

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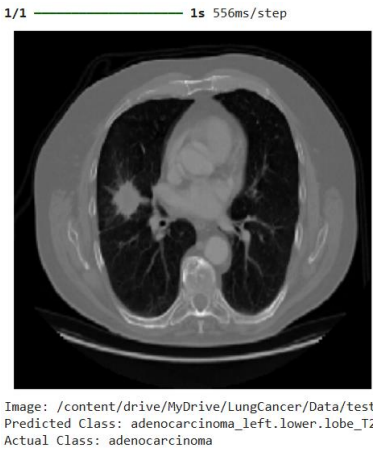

Fig. 12. Classified input Image

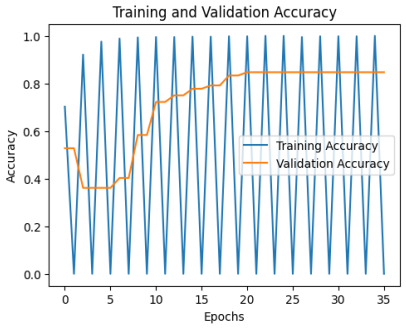

Fig. 13. Training and Validation Accuracy (Training Phase)

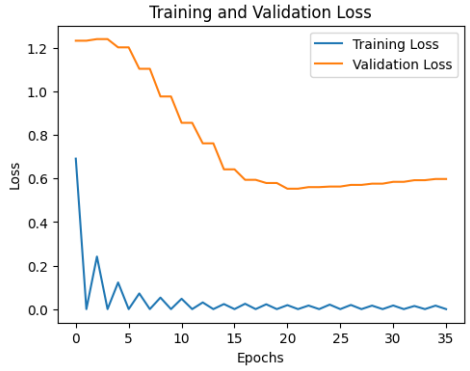

Fig. 14. Training and Validation Loss (Training Phase)

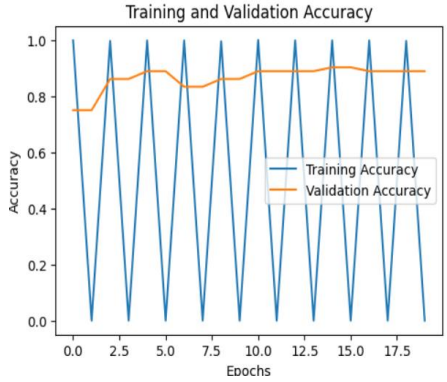

Fig. 15. Training and Validation Accuracy (Fine Tuning Phase)

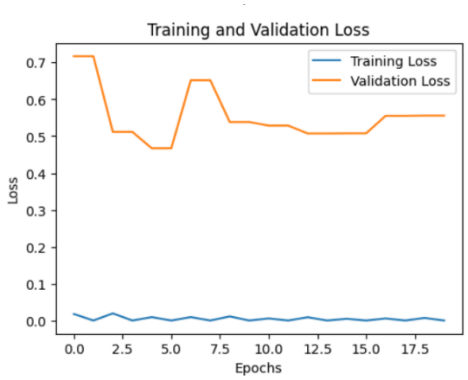

Fig. 16. Training and Validation Loss (Fine Tuning Phase)

VI. CONCLUSION

The developed deep learning model, leveraging the VGG16 architecture, demonstrated high accuracy and reliability in classifying lung CT scan images into four categories. The model achieved significant performance metrics during training and testing, highlighting its ability to assist in early lung cancer diagnosis. This tool has the potential to reduce diagnostic errors, accelerate detection, and improve patient outcomes by providing consistent and reliable predictions.

However, while the model performs well on the given dataset, there remains room for improvement in addressing certain limitations, such as variations in CT scan quality, class imbalances, and generalizability across diverse patient populations. These aspects are crucial for ensuring its efficacy in real-world applications.

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