LUNG CANCER CLASSIFICATION WITH DEEP LEARNING

A PROJECT REPORT

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CERTIFICATE

This is to certify that the project report entitled, **Lung Cancer Classification with Deep Learning** submitted by **Safwa Nizamudeen (Reg. No. TKM23MCA-2052)**, to TKM College of Engineering, affiliated with APJ Abdul Kalam Technological University, in partial fulfillment of the requirements for the award of the Degree of Master of Computer Application, is a bonafide record of the project work carried out by her under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

Internal Supervisor Head of the Department External Examiner

DECLARATION

I undersigned hereby declare that the project report **Lung Cancer Classification with Deep Learning** submitted for partial fulfillment of the requirements for the award of degree of Master of Computer Application of the APJ Abdul Kalam Technological University, Kerala, is a bonafide work done by me under supervision of Prof. Natheera Beevi M. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

Place: Kollam   Safwa Nizamudeen

Date: 02/04/2025

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ABSTRACT

Lung cancer is one of the leading causes of death worldwide, making early detection critical for improving survival rates. This project focuses on developing a deep learning-based multi-class classification system for lung cancer detection using CT scan images. The project aims to enhance the diagnostic process by applying advanced image processing techniques and deep learning models. Initially, image enhancement is performed using Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve the visibility of key features in CT scans. Data augmentation is then applied to increase the diversity of training data.

Several convolutional neural network (CNN)-based architectures, including VGG19, ResNet50, and ConvNeXtSmall, are trained on the augmented dataset. The performance of each model is evaluated, with ConvNeXtSmall emerging as the best-performing model, demonstrating superior accuracy in classifying four categories of lung cancer: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal lung tissue. The use of transfer learning and pretrained models further improves classification performance.This project highlights the potential of deep learning techniques in enhancing the accuracy and efficiency of lung cancer diagnosis.

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Chapter 1

INTRODUCTION

Lung cancer remains one of the leading causes of cancer-related deaths worldwide, with its aggressive nature and late-stage detection contributing to high mortality rates. Early diagnosis plays a crucial role in improving patient survival, as timely medical intervention can significantly enhance treatment outcomes. Traditionally, lung cancer detection relies on radiologists manually analyzing CT scan images, a process that requires significant expertise and time. To address these challenges, researchers have turned to artificial intelligence (AI) and deep learning techniques to develop automated and more reliable diagnostic solutions.

This project presents a deep learning-based approach for multi-class classification of lung cancer using CT scan images. The methodology begins with preprocessing the images using Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance contrast and improve feature visibility. Additionally, data augmentation techniques are applied to increase dataset diversity. Several Convolutional Neural Network (CNN) architectures, including VGG19, ResNet50, and ConvNeXtSmall, are trained and evaluated for their performance in distinguishing between four categories: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal lung tissue. By using deep learning and image preprocessing techniques, this study aims to develop an accurate and efficient classification model for lung cancer detection.

The significance of this work lies in its potential to enhance the diagnostic process by automating classification with high precision, reducing the burden on radiologists, and minimizing diagnostic errors. The use of deep learning models trained on enhanced and augmented CT images allows for improved detection of cancer, ultimately contributing to early-stage diagnosis and better patient outcomes. The findings from this study highlight the effectiveness of advanced AI-driven approaches in medical imaging and reinforce the importance of integrating deep learning techniques into modern healthcare systems. By improving accuracy and efficiency, this project aims to bridge the gap between traditional diagnostic methods and AI-powered automation in lung cancer detection.

1.1 Existing Systems

Lung cancer detection traditionally relies on radiologists manually analyzing CT scan images to identify cancerous lesions. While this method is widely used, it is time-consuming, highly dependent on the radiologist's expertise, and susceptible to human error. To assist in diagnosis, Computer-Aided Diagnosis (CAD) systems have been developed, using machine learning techniques to help detect abnormalities. However, many of these systems primarily focus on binary classification, distinguishing only between cancerous and non-cancerous cases. This limitation makes it difficult to differentiate between specific lung cancer types, such as adenocarcinoma, large cell carcinoma, and squamous cell carcinoma, which require distinct treatment strategies.

Some existing deep learning approaches utilize CNN-based models for lung cancer detection, but they often struggle with challenges such as poor image quality, class imbalance, and insufficient training data. Additionally, many systems lack proper image enhancement techniques, which are crucial for improving feature visibility in medical images. The absence of standardized preprocessing and the limited ability of traditional models to handle complex lung cancer patterns highlight the need for an improved classification approach that integrates advanced deep learning techniques, image enhancement, and data augmentation for better accuracy and reliability.

1.2 Problem Statement

Traditional diagnostic methods rely on radiologists manually analyzing CT scan images, which is a time-consuming process and highly dependent on human expertise. This can lead to inconsistencies in diagnosis, delays in treatment, and potential misclassification of cancer types. While Computer-Aided Diagnosis (CAD) systems have been introduced to assist in detection, many existing models focus only on binary classification (cancerous vs. non-cancerous) and lack the ability to accurately distinguish between multiple lung cancer subtypes. This limitation prevents precise identification of adenocarcinoma, large cell carcinoma, and squamous cell carcinoma, which is essential for effective treatment planning.

Moreover, many current deep learning-based approaches do not incorporate advanced image preprocessing techniques, leading to challenges in feature extraction from CT scans. Poor image quality, noise, and contrast variations can significantly impact model performance. Additionally, the absence of adequate data augmentation techniques limits the generalization ability of deep learning models, increasing the risk of overfitting and reducing classification accuracy. To address these challenges, this project proposes a deep learning-based multi-class classification system that enhances CT scan images using Contrast Limited Adaptive Histogram Equalization (CLAHE) and applies data augmentation for better model generalization. By leveraging CNN architectures such as VGG19, ResNet50, and ConvNeXtSmall, this system aims to achieve high accuracy in lung cancer classification, providing a reliable and efficient diagnostic tool.

1.3 Proposed System

To overcome the limitations of traditional diagnostic methods and existing deep learning-based models, this project introduces an advanced deep learning-based multi-class lung cancer classification system using CT scan images. The proposed system integrates image enhancement, data augmentation, and state-of-the-art deep learning architectures to improve the accuracy and efficiency of lung cancer detection. By using Contrast Limited Adaptive Histogram Equalization (CLAHE), the system enhances CT scan images to improve contrast and highlight essential features, ensuring better feature extraction during model training. Additionally, data augmentation techniques are applied to increase dataset variability.

To overcome the limitations of traditional diagnostic methods and existing deep learning-based models, this project introduces an advanced deep learning-based multi-class lung cancer classification system using CT scan images. The proposed system integrates image enhancement, data augmentation, and state-of-the-art deep learning architectures to improve the accuracy and efficiency of lung cancer detection. By leveraging Contrast Limited Adaptive Histogram Equalization (CLAHE), the system enhances CT scan images to improve contrast and highlight essential features, ensuring better feature extraction during model training. Additionally, data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset variability, reducing overfitting and improving the generalization capability of the model.

1.4 Objectives

The primary objective of this project is to develop an AI-driven deep learning model for accurate multi-class classification of lung cancer using CT scan images. The specific objectives include:

- To enhance image quality using Contrast Limited Adaptive Histogram Equalization (CLAHE) – Improve contrast and visibility of features in CT scan images to ensure better tumor detection.

- To apply data augmentation techniques – Implement transformations to expand the dataset.

- To train and evaluate multiple deep learning models – Utilize CNN architectures including VGG19, ResNet50, and ConvNeXtSmall to classify lung cancer into four categories: adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal lung tissue.

- To identify the best-performing model for classification – Compare the accuracy and efficiency of different models and select the one that provides the highest classification performance.

- To develop an automated lung cancer classification system – Reduce dependency on manual diagnosis by implementing an AI-powered solution that assists radiologists in making quicker and more reliable decisions.

- To integrate the model into a user-friendly interface – Ensure ease of use for medical professionals by designing an intuitive system that facilitates efficient lung cancer detection.

By achieving these objectives, this project aims to contribute to the advancement of deep learning in medical imaging, providing an effective and automated solution for lung cancer diagnosis.

Chapter 2

LITERATURE SURVEY

The literature survey provides an overview of existing research and advancements in lung cancer classification using deep learning. It explores various machine learning and deep learning techniques applied in medical imaging for cancer detection.Lung cancer detection has been a significant area of research in the field of medical imaging, with early methods relying on traditional Computer-Aided Diagnosis (CAD) systems and manual analysis by radiologists. Additionally, many of these methods focused on binary classification (cancerous vs. non-cancerous) rather than distinguishing between different lung cancer subtypes, which is essential for precise diagnosis and treatment. The need for a more reliable and automated approach has led to the adoption of deep learning techniques, particularly Convolutional Neural Networks (CNNs), which have significantly improved classification accuracy.

Image preprocessing techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) have been introduced to enhance image quality, making tumor regions more distinguishable. Despite these advancements, challenges such as insufficient data augmentation, overfitting, and model generalization issues remain. This literature survey explores various deep learning-based approaches for lung cancer classification, highlighting their strengths, limitations, and the scope for further improvements. By analyzing existing research, this study aims to develop an optimized deep learning model that integrates advanced CNN architectures, image enhancement, and augmentation techniques for more accurate multi-class lung cancer detection.

2.1 Related Works

2.1.1 Lung cancer disease prediction with CT scan and histopathological images feature analysis using deep learning techniques.

One of the significant studies in lung cancer classification is conducted by Vani Rajasekar et al. in the paper. This research, published in Results in Engineering (2023), explores the application of deep learning models in lung cancer detection using CT scan and histopathological images. The authors employed various Convolutional Neural Network (CNN) architectures, including VGG16, VGG19, Inception V3, and ResNet50, to classify lung cancer images effectively.

The study demonstrated high accuracy and comprehensive analysis across multiple image types, making it a significant contribution to lung cancer classification. However, the research primarily focused on binary classification (cancerous vs. non-cancerous), limiting its capability to differentiate between multiple lung cancer subtypes. Additionally, the lack of image enhancement techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) could have impacted the clarity of tumor regions in CT scan images. This highlights the necessity for further improvements by incorporating image preprocessing and multi-class classification techniques to enhance detection accuracy and reliability. [1]

2.1.2 Deep Learning Techniques for Lung Cancer Recognition

The study conducted by Vemula S.T, Sreevani M, Rajarajeswari P, Bhargavi K, Tavares, and Alankritha S explores the application of CNN, VGG16, and VGG19 models for lung cancer detection. The research applies data augmentation techniques to enhance the dataset and achieves an impressive accuracy of about 95% in classifying lung cancer images.

Despite the high accuracy, the study primarily focuses on binary classification (cancerous vs. non-cancerous) rather than multi-class classification, limiting its ability to distinguish between different lung cancer subtypes. Additionally, the research does not explore advanced deep learning models such as ResNet or ConvNeXt, which could further improve classification performance. This highlights the need for a more robust system that integrates multi-class classification and advanced deep learning models for enhanced lung cancer detection accuracy. [2]

2.1.3 Lung-EffNet: Lung Cancer Classification Using EfficientNet from CT-Scan Images

Rehan Raza et al. proposed a deep learning-based approach for lung cancer classification using EfficientNetB1. The study focused on improving classification accuracy using convolutional neural networks (CNNs) and addressing class imbalance through data augmentation techniques. Their model achieved high accuracy, demonstrating the effectiveness of EfficientNet-based architectures in detecting lung cancer from CT scan images.

However, the study lacked a comparative analysis with other advanced deep learning models, which limits the understanding of EfficientNetB1's relative performance. While this research highlights the importance of data augmentation, the present work extends beyond it by exploring multiple architectures such as ResNet50, VGG19 and ConvNeXtSmall to provide a more comprehensive evaluation of lung cancer classification. [3]

2.1.4 Deep Learning-Based Lung Cancer Classification of CT Images Using Augmented Convolutional Neural Network

Bushara et al. proposed a deep learning-based lung cancer classification system using Convolutional Neural Networks (CNNs) with data augmentation techniques. Their study achieved an accuracy of approximately 95%, demonstrating the effectiveness of data augmentation in improving model performance. However, the research lacked image enhancement techniques, which could further optimize classification accuracy.

Additionally, the study did not include a comparative analysis with other deep learning models, limiting insights into its relative performance. Despite these limitations, the work highlights the potential of CNNs in lung cancer detection and reinforces the importance of preprocessing techniques in medical image classification. [4]

2.1.5 Lung Cancer Detection Based on CT Scan Images By Using Deep Transfer Learning

The study by Tulasi et al. (n.d.) used transfer learning with AlexNet, GoogleNet, and ResNet50 for lung cancer classification, achieving high accuracy through feature extraction and dropout techniques. Their use of Frangi filtering improved image clarity, aligning with our project's focus on preprocessing techniques like CLAHE.

However, their approach was limited to binary classification, while our project performs multi-class classification of lung cancer subtypes. Additionally, they did not explore multiple architectures together, whereas we compare VGG19, ResNet50, and ConvNeXtSmall for optimal performance. Their lack of extensive data augmentation also affected model robustness, which our project addresses to enhance classification accuracy and reliability. [5]

2.1.6 A Deep Learning Approach to Detect and Classification of Lung Cancer

Khatun et al. (2023) explored lung cancer classification using deep learning, achieving a high accuracy of 98% with ResNet50 on histopathological images. Their study highlights the effectiveness of CNN-based architectures for distinguishing between benign and malignant lung tissues. However, their dataset primarily consists of histopathology images, whereas our research focuses on CT scan images for lung cancer classification. Unlike their approach, which includes EfficientNet and MobileNetV2, our study employs ConvNeXtSmall alongside VGG19 and ResNet50, leveraging their advanced feature extraction capabilities. Additionally, we enhance image quality using Contrast Limited Adaptive Histogram Equalization (CLAHE) before classification, improving feature visibility in CT scans.

Despite achieving high accuracy, Khatun et al.'s study does not address critical challenges such as feature enhancement and noise reduction, which are essential for medical imaging tasks. Their dataset size is also relatively small, consisting of 750 lung tissue images, whereas our study utilizes a larger CT scan dataset with multiple lung cancer subtypes. Furthermore, their methodology does not incorporate preprocessing techniques like CLAHE, which can significantly enhance model performance on medical imaging data. By focusing on CT scans and integrating preprocessing techniques, our research aims to improve lung cancer classification accuracy while addressing the limitations observed in prior studies. [6]

Chapter 3

METHODOLOGY

3.1 Introduction

Lung cancer classification using deep learning has gained significant attention due to its potential to assist medical professionals in early diagnosis. This study employs Convolutional Neural Networks (CNNs) and transfer learning techniques to classify lung cancer from computed tomography (CT) scan images. The methodology is designed to enhance classification accuracy by incorporating image preprocessing, augmentation, and advanced deep learning architectures.

The proposed system utilizes a dataset containing images of different lung cancer types, including adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal lung tissue. Several deep learning models, such as ResNet50, VGG19, ConvNeXtSmall, and EfficientNetB4, are implemented and compared based on their performance. The study also applies image enhancement techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) and data augmentation to improve model robustness.

To ensure reliable predictions, the dataset is divided into training, validation, and testing sets. The models are trained using transfer learning to leverage pretrained knowledge for improved feature extraction. Various performance metrics, including accuracy, precision, recall, and F1-score, are used to evaluate the models. The final optimized model is integrated into a Streamlit-based interface, allowing for easy interaction and visualization of classification results.

This methodology provides a structured approach to lung cancer classification by combining state-of-the-art deep learning models with effective preprocessing techniques, ensuring high accuracy and robustness in real-world applications.

3.2 System Architecture

The proposed system for lung cancer classification using deep learning consists of multiple interconnected stages, ensuring an efficient and accurate classification process. The architecture is designed to take CT scan images as input, enhance their quality using image preprocessing techniques, train deep learning models, and classify lung cancer into four categories: adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal lung tissue. The system integrates Contrast Limited Adaptive Histogram Equalization (CLAHE) for image enhancement, data augmentation to improve model generalization, and multiple deep learning architectures (CNN, VGG19, ResNet50, and ConvNeXtSmall) for classification.

3.2.1 System Workflow

The workflow of the system can be divided into the following steps:

- **Image Acquisition:** The CT scan images used in this study were obtained from the publicly available Kaggle dataset, Chest CT Scan Images Dataset (Mohamed Hany, Kaggle).

- **Image Preprocessing:** Applying CLAHE for contrast enhancement.

- **Data Augmentation:** Applying transformations to artificially expand the dataset.

- **Model Selection and Training:** Training CNN, VGG19, ResNet50, and ConvNeXtSmall models. Then fine-tuning hyperparameters to improve performance.

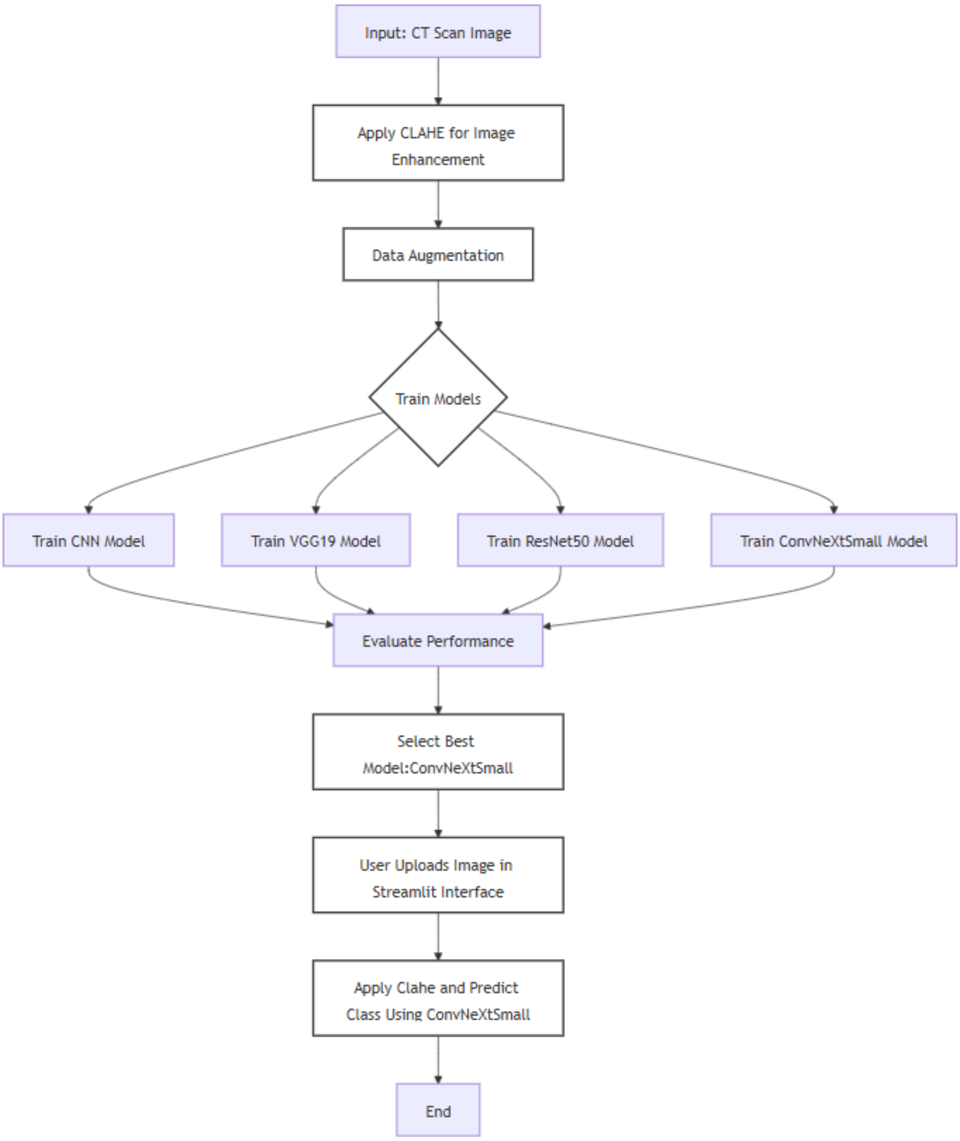

Figure 3.1: System Workflow Diagram

- **Model Evaluation:** Comparing model performance using accuracy, precision, recall.

- **Prediction, Classification, and Deployment:** Deploying the best-performing model (ConvNeXtSmall) for classifying lung cancer from new CT scan images.Implementing a Streamlit-based interface to allow medical professionals to upload CT scans, process them, and view classification results in real time.

Figure 3.1 illustrates the system workflow, depicting the step-by-step process from image acquisition to final classification and deployment.

3.3 Dataset Description

The dataset used in this project consists of 1,000 CT scan images categorized into four classes:

- Adenocarcinoma: 348 images
- Large Cell Carcinoma: 187 images
- Squamous Cell Carcinoma: 260 images
- Normal: 215 images

The dataset is divided into three subsets to ensure effective model training and evaluation:

- Training Set: Used to train the deep learning models.
- Validation Set: Helps in tuning hyperparameters and preventing overfitting.
- Testing Set: Used for final evaluation to assess model generalization.

The dataset is sourced from Kaggle: "Chest CT Scan Images Dataset" (https://www.kaggle.com/dat ctscan-images/), and it provides a diverse set of lung cancer CT scan images, ensuring robustness in model performance. The balanced distribution of images across different categories allows the deep learning models to learn distinct features of each lung cancer type effectively.

3.3.1 Lung Cancer Types in the Dataset

Lung cancer is classified into different subtypes based on the appearance of cancer cells under a microscope. The dataset includes three types of lung cancer:

- **Adenocarcinoma:** This is the most common subtype of lung cancer, typically forming in the outer regions of the lungs. It arises from mucus-producing glandular cells and is often found in non-smokers and younger patients. Adenocarcinoma is known for its slow growth compared to other lung cancer types but can spread to distant organs if not detected early.

- **Squamous Cell Carcinoma:** This type of lung cancer develops in the squamous epithelial cells lining the airways. It is often associated with smoking and tends to form in the central parts of the lungs, near the bronchi. Squamous cell carcinoma is aggressive and can cause airway obstruction, leading to symptoms such as coughing and breathing difficulties.

- **Large Cell Carcinoma:** Large cell carcinoma is an undifferentiated type of lung cancer that appears as large, abnormal-looking cells under a microscope. It can develop anywhere in the lungs and tends to grow rapidly, making it more challenging to treat. Unlike adenocarcinoma and squamous cell carcinoma, large cell carcinoma does not have specific cellular features, making its classification more general.

These classifications play a crucial role in medical diagnosis and treatment planning, as different lung cancer types respond to different treatment approaches.

3.4 Image Preprocessing

3.4.1 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a powerful image enhancement technique used to improve the visibility of important features in medical images. Traditional Histogram Equalization (HE) enhances contrast globally, which can lead to over-enhancement and noise amplification, especially in homogeneous regions. CLAHE overcomes this issue by applying localized contrast adjustments while maintaining smooth transitions across the image.

Working of CLAHE

- **Dividing the Image into Small Regions (Tiles):** The image is split into smaller, non-overlapping blocks (tiles), typically of size 8×8 or 16×16 pixels.
- **Histogram Computation:** A histogram is generated for each tile, showing the distribution of pixel intensities.
- **Contrast Enhancement with Clipping:** A predefined contrast limit (clip limit) is applied to prevent excessive contrast stretching in uniform regions. This reduces noise while enhancing meaningful features.
- **Histogram Redistribution:** The pixel intensities within each tile are adjusted based on the modified histogram to improve contrast.
- **Bilinear Interpolation:** To ensure smooth transitions between adjacent tiles, CLAHE uses interpolation to avoid artificial edges.

Advantages of CLAHE in Medical Imaging

- Enhances local contrast without distorting the overall image structure.
- Preserves fine details, making subtle abnormalities in CT scans more visible.
- Reduces noise amplification, which is crucial in medical images where excessive contrast enhancement can introduce false features.
- Improves feature extraction for deep learning models by making lung nodules and cancerous regions more distinguishable.

Given its effectiveness, CLAHE is widely used in medical imaging applications, including lung cancer classification, where precise contrast enhancement is essential for accurate diagnosis.

3.4.2 Image Preprocessing Using CLAHE

In this project, CLAHE is applied to enhance the visibility of lung structures in CT scan images before they are fed into deep learning models. The preprocessing steps are as follows:

1. **Gray-Scale Conversion:** Since CT scans are inherently grayscale and do not contain color information, converting them to grayscale simplifies the processing pipeline. This step reduces computational complexity while retaining all necessary structural details.

2. **Applying CLAHE:** CLAHE is used to enhance the local contrast of grayscale images. The following parameters are chosen:

    - Clip Limit: 1.5 (prevents excessive contrast enhancement and noise amplification).
    - Tile Grid Size: (8,8) (ensures localized contrast enhancement while maintaining smooth transitions between tiles).

    This step highlights subtle differences in lung tissues, making abnormalities such as tumors more distinguishable for deep learning models.

3. **Noise Reduction Using Gaussian Blur:** After CLAHE, a Gaussian Blur filter (3×3 kernel) is applied to reduce noise and smoothen the image while preserving essential edges.

    - Why Gaussian Blur? CLAHE can sometimes introduce minor noise in homogeneous regions. Applying Gaussian Blur helps in minimizing noise while keeping important structures intact.

- Effect on Deep Learning Models: This step ensures that the deep learning model focuses on meaningful features rather than unwanted noise, improving classification performance.

By applying these preprocessing techniques, the system ensures that the deep learning models receive high-quality input images, leading to improved classification accuracy and more reliable predictions.

Figure 3.2 depicts the effect of CLAHE on CT scan images, showing a comparison between the original image and the enhanced version after applying CLAHE. The improved contrast highlights subtle differences in lung structures, aiding in better feature extraction for deep learning-based classification.

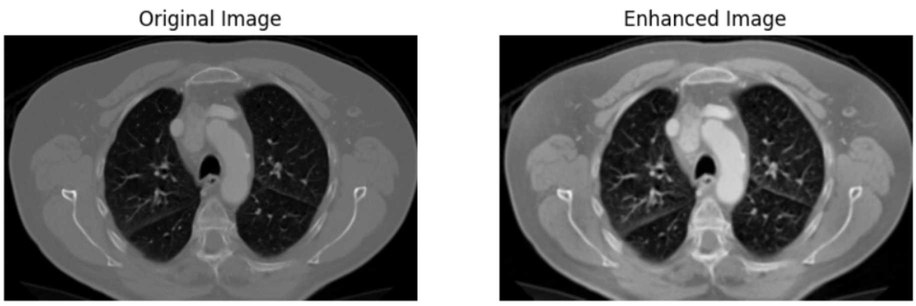

Figure 3.2: CT Scan Image Before and After CLAHE

3.5 Data Augmentation Techniques

Data augmentation plays a crucial role in deep learning-based medical image analysis, especially when dealing with limited datasets. In this project, augmentation is applied to artificially expand the training set, enhancing the model's ability to generalize across different variations of lung CT scans. Since medical datasets often suffer from class imbalances and scarcity of images, augmentation helps prevent overfitting by introducing subtle yet meaningful transformations to the original images.

The augmentation pipeline is implemented using the Albumentations library, a powerful image processing tool known for its efficiency and flexibility in deep learning applications.To maintain the integrity of medical features after augmentation, Structural Similarity Index (SSIM) is used to measure the similarity between original and augmented images. The SSIM score evaluates how closely the augmented image retains the structural information of the original. A high SSIM score indicates that the augmentation process preserves critical diagnostic features while introducing meaningful variations.

To ensure that the model learns robust features without overfitting to specific patterns, augmentation is selectively applied only to the training dataset, while validation and test sets remain unchanged to preserve their role in unbiased model evaluation. The augmentation techniques used in this project include:

1. Horizontal Flipping
    - Randomly flips images along the horizontal axis.
    - Introduces variations in lung nodule orientations.
    - Helps the model recognize features regardless of left-right positioning.
2. Random Brightness and Contrast Adjustment
    - Slightly modifies the brightness and contrast of images.
    - Simulates variations in imaging conditions across different CT scan machines and settings.
    - Ensures that the model learns features independent of illumination differences.
3. Multiple Augmentations Per Image
    - Each image in the training dataset undergoes three different augmentations, increasing dataset diversity.

- Augmented images retain essential lung nodule characteristics while exhibiting variations in orientation and intensity.

By employing these augmentation techniques, the dataset becomes more diverse and representative of real-world variations in lung CT scans.The dataset size increases from 1010 to 2879 CT scan images by only applying augmentations to training dataset. This enhances the model's ability to recognize patterns across different patients, improving its classification accuracy and robustness.

3.6 Deep Learning Models

Deep learning, a subset of machine learning, has revolutionized the field of medical image analysis by enabling automated feature extraction and high-accuracy classification. Unlike traditional machine learning approaches that rely on handcrafted features, deep learning models learn hierarchical representations directly from raw data, making them highly effective for complex tasks such as lung cancer detection from CT scan images.

In this project, deep learning models are employed to classify lung cancer into multiple categories based on CT scan images. These models leverage Convolutional Neural Networks (CNNs) and advanced architectures such as VGG19, ResNet50, and ConvNeXtSmall, each designed to extract meaningful patterns from medical images.

The key advantages of deep learning for lung cancer classification are:

- **Automated Feature Extraction:** Deep learning eliminates the need for manual feature selection by learning features directly from images.
- **High Accuracy and Robustness:** CNN-based architectures outperform traditional methods in detecting subtle patterns in medical scans.

- **Generalization Capability:** Transfer learning with pretrained models enhances the ability to classify new, unseen images.
- **Efficient Processing:** Deep learning accelerates the diagnosis process, assisting radiologists in decision-making.

3.6.1 Convolutional Neural Networks(CNN)

Convolutional Neural Networks (CNNs) are a specialized class of deep learning models designed for image analysis. CNNs are highly effective for lung cancer classification as they can automatically detect spatial patterns in CT scan images, making them ideal for medical image processing. They automatically detect spatial patterns in CT scan images, aiding in medical image processing. The Convolutional Layer extracts essential features like edges and tumor boundaries using filters (kernels). To introduce non-linearity, the ReLU activation function replaces negative values with zero, enabling the network to learn complex patterns. The Pooling Layer (Max Pooling) reduces spatial dimensions while retaining crucial information, enhancing dominant features and ignoring irrelevant details.

After feature extraction, the Fully Connected (FC) Layer flattens the features into a one-dimensional vector to learn relationships between extracted patterns and classification labels (e.g., adenocarcinoma, squamous cell carcinoma, large cell carcinoma, or normal lung tissue). The final Softmax Layer outputs the probability distribution across cancer types, enabling accurate predictions. This structured approach allows CNNs to effectively analyze CT scan images for lung cancer detection and classification.

3.6.1.(i) CNN Training Strategy

The CNN model implemented in the project follows a deep architecture with multiple convolutional layers, batch normalization, dropout layers, and dense layers to enhance generalization and prevent overfitting. It consists of four convolutional blocks with increasing filter sizes (64, 128, 256, 512). Each block includes:

- ReLU activation for non-linearity
- Batch normalization to stabilize training
- Max pooling (2×2) for dimensionality reduction
- Dropout layers (0.25 to 0.4) to prevent overfitting

The fully connected layers include a flatten layer, two dense layers (512 and 256 neurons) with L2 regularization, batch normalization, and dropout (0.45–0.5). The final Softmax layer performs multi-class classification.

To improve model generalization, data augmentation techniques like rotation, zoom, brightness variation, and channel shifting are applied. A dynamic learning rate schedule (warm-up and cosine decay) is used .Training optimizations include early stopping, model checkpointing, and learning rate reduction on plateau. Evaluation metrics such as test accuracy, classification report (precision, recall, F1-score), and confusion matrix provide insights into model performance and areas for improvement.

3.6.2 VGG19

VGG19 is a deep Convolutional Neural Network (CNN) known for its simple yet highly effective architecture. Developed by the Visual Geometry Group at Oxford, VGG19 consists of 19 layers, including convolutional and fully connected layers. It is widely used for medical image classification due to its ability to learn complex spatial features and hierarchical representations.

VGG19 follows a uniform design with small (3×3) convolutional filters, enabling deep feature extraction while maintaining computational efficiency. The architecture consists of 16 convolutional layers arranged in five blocks, each utilizing the ReLU activation function to introduce non-linearity and enhance feature learning. Max pooling is applied after each block to reduce spatial dimensions while preserving essential features, ensuring efficient computation. The network concludes with three fully connected layers, where the final layer employs a softmax activation function for multi-class classification. Additionally, dropout regularization is incorporated in the fully connected layers to prevent overfitting and improve model generalization.

3.6.2.(i) **VGG19 Training Strategy**

A pre-trained VGG19 model was used for the lung classifictaion task, leveraging ImageNet weights while excluding the top layers. The network was fine-tuned in a two-phase training strategy.

Initially, all layers in VGG19 were frozen, allowing only the newly added fully connected layers to be trained. A sequential model was built, integrating a Global Average Pooling layer, followed by fully connected layers with 512, 256, and 128 neurons, each activated using ReLU. Batch normalization and dropout were applied to enhance generalization. The final classification layer consisted of four output neurons with softmax activation, corresponding to the four lung cancer categories: adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal tissue.

To improve training stability, categorical cross-entropy was used as the loss function, and the Adam optimizer with an initial learning rate of 1e-4 was selected. The training was conducted using enhanced data augmentation, including rotation, width and height shifts, shearing, zooming, brightness adjustments, and horizontal flips. The early stopping and learning rate reduction callbacks were used to optimize the training process.

After the initial training phase, the last ten layers of VGG19 were unfrozen to allow fine-tuning of deeper convolutional features. The learning rate was reduced to 1e-5, and the model was retrained to enhance performance while avoiding overfitting. The same loss function and optimizer were used, and early stopping and learning rate reduction were again applied. The best model was saved using model checkpointing and later evaluated on the test dataset. Performance was measured in terms of accuracy, precision, and recall. The training process was visualized using accuracy and loss plots across both training phases.

3.6.3 ResNet50

ResNet50 (Residual Network 50) is a deep convolutional neural network (CNN) that is widely used for image classification tasks. It is part of the ResNet family developed by Microsoft, designed to solve the vanishing gradient problem in deep networks. ResNet50 consists of 50 layers, including convolutional, pooling, and fully connected layers, with a unique feature called residual connections.

ResNet50 follows a deep residual learning framework that includes several key components. Convolutional layers extract hierarchical features, while batch normalization speeds up training and stabilizes learning. The ReLU activation function introduces non-linearity, enabling the network to learn complex patterns. To reduce overfitting, a Global Average Pooling (GAP) layer is used, which reduces feature maps to a single value per feature. The final fully connected layers perform classification into four lung cancer categories, and the softmax output layer converts logits into probability scores for multi-class classification.

A key innovation in ResNet50 is the residual block, represented as $y = F(x) + x$, where x is the input to a residual block and $F(x)$ represents the transformation applied, including convolution, batch normalization, and ReLU activation. This residual connection allows information to flow smoothly through the network, mitigating the vanishing gradient problem and enabling deeper network training.

3.6.3.(i) **ResNet50 Training Strategy**

The training process is divided into two phases to optimize performance efficiently. Initially, the pre-trained ResNet50 layers are frozen to retain the rich feature representations learned from ImageNet. A custom classifier is added on top, comprising fully connected layers with dropout and batch normalization to minimize overfitting. The model is compiled using the AdamW optimizer with a learning rate of 1×10^3. Categorical Cross-Entropy with label smoothing (0.1) is used to improve generalization. To enhance performance, data augmentation techniques such as rotation, zoom, and brightness adjustment are applied. Early stopping prevents unnecessary training, while ReduceLROnPlateau dynamically lowers the learning rate when the model performance plateaus.

Once the top layers are trained, the last 50 layers of ResNet50 are unfrozen for fine-tuning. A smaller learning rate (1×10) and weight decay (1×10) are used to ensure that the pre-trained weights are not drastically altered. The model is retrained for 15 additional epochs, allowing it to refine high-level feature representations.The model is evaluated on a test set using key metrics: accuracy precision and recall and a confusion matrix. The training process was visualized using accuracy and loss plots across both training phases.

3.6.4 ConvNeXtSmall

ConvNeXtSmall is a modern convolutional neural network (CNN) designed to improve image classification while maintaining the efficiency of traditional CNNs. Inspired by Vision Transformers (ViTs), it incorporates advanced techniques such as depthwise convolutions and Layer Normalization to enhance performance.

ConvNeXtSmall consists of multiple stages with convolutional layers, normalization layers, and activation functions, replacing batch normalization with Layer Normalization for better training stability. It incorporates depthwise separable convolutions enhancing feature extraction. The model adopts a patchify stem similar to Vision Transformers (ViTs), where the input image is divided into patches before being processed. An efficient downsampling mechanism maintains a balance between spatial resolution and computational efficiency, while its fully convolutional, hierarchical design makes it well-suited for lung cancer classification. The final classification layers apply Global Average Pooling (GAP) to aggregate spatial information, followed by fully connected layers and a softmax activation function to classify images.

3.6.4.(i) **ConvNeXtSmall Training Strategy**

The training strategy for the lung cancer classification model follows a two-phase approach.The lung cancer classification model follows a two-phase training strategy to ensure efficient feature extraction and fine-tuning for optimal accuracy. Initially, uses ConvNeXtSmall as a frozen feature extractor, leveraging its pre-trained knowledge from ImageNet to reduce overfitting on the limited medical dataset. Custom dense layers with batch normalization, dropout, and L2 regularization are added for better generalization. The model is trained using AdamW optimizer with initial learning rate of 1e-3. Augmentation techniques like rotation, shifting, and brightness variations further improve generalization while maintaining medical imaging constraints. Early stopping is used to prevent overfitting.

In the fine-tuning phase, we unfreeze the last 50 layers of ConvNeXtSmall, allowing it to adapt high-level features to lung cancer detection. The learning rate is reduced to 1e-6 to retain pre-trained knowledge. The model is retrained with class-weighted cross-entropy loss, monitored for validation accuracy improvements. For evaluation, the model is tested on an unseen dataset using accuracy, precision, recall, and F1-score. A confusion matrix visualizes classification errors for medical interpretability. The trained model is saved for deployment in clinical applications.

3.7 Prediction and Deployment

After extensive training and evaluation of multiple deep learning models, ConvNeXtSmall was identified as the best-performing model for lung cancer classification, achieving an impressive accuracy of 92.70%. Given its high accuracy compared to others, the ConvNeXtSmall model was selected for deployment, ensuring that medical professionals and researchers can utilize it for real-world lung cancer detection. The deployment was implemented using Streamlit, a lightweight yet powerful web application framework that allows users to interact with the trained model efficiently.

3.7.1 Prediction Phase

The prediction phase is a critical component of the system, allowing new CT scan images to be classified into one of the four lung cancer categories: adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal lung tissue. This phase consists of several key steps to ensure accurate and reliable classification.

The process begins with image upload, where the user selects and uploads a CT scan image through the Streamlit-based interface. Once the image is uploaded, it undergoes preprocessing, a crucial step to enhance image quality and improve classification accuracy. The preprocessing pipeline involves converting the image to grayscale to reduce computational complexity while preserving essential structural details. Then, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance the local contrast of the CT scan, making fine details more visible and improving feature extraction for the model. After contrast enhancement, the image is resized to match the input dimensions required by the ConvNeXtSmall model, ensuring consistency across all input samples.

Following preprocessing, the preprocessed image is passed to the trained ConvNeXtSmall model, which extracts deep features from the CT scan and performs classification. The model analyzes patterns and textures within the image and assigns it to one of the four lung cancer categories. The output consists of the predicted class along with a confidence score, which indicates the certainty of the classification result. Higher confidence scores suggest a more reliable prediction, aiding medical professionals in decision-making.

3.7.2 Deployment using Streamlit

The deployment of the lung cancer classification model was implemented using Streamlit, an open-source framework designed for developing interactive machine learning applications. Streamlit was chosen for its simplicity, efficiency, and ease of integration with deep learning models, allowing for the seamless deployment of the trained ConvNeXtSmall model.

The deployment process began with the creation of an interactive web interface, where users can effortlessly upload CT scan images for analysis. The interface is designed to be intuitive and user-friendly, ensuring that both medical professionals and non-technical users can navigate it with ease. Once an image is uploaded, it is automatically preprocessed using CLAHE-based contrast enhancement, resized, and passed to the trained model for classification.

The backend of the application integrates the pretrained ConvNeXtSmall model, ensuring real-time execution for image classification. The model is optimized for fast inference, allowing predictions to be generated within seconds. The classification results, including the predicted lung cancer type and confidence score, are displayed immediately on the web interface.

3.8 Software Requirements and Specifications

The software requirements and specifications define the essential tools, frameworks, and system configurations necessary for the development, training, evaluation, and deployment of the lung cancer classification model.These components provide functionalities for deep learning, image preprocessing, data handling, and web-based deployment.

3.8.1 Software Requirements

- **Programming Language:** Python is the primary programming language used in this project due to its extensive support for machine learning and deep learning libraries, ease of use, and strong community support.
- **Deep Learning Frameworks:**
  - TensorFlow: TensorFlow is an open-source deep learning framework developed by Google. It provides tools for building, training, and deploying deep learning models efficiently.
  - Keras: Keras is a high-level API running on top of TensorFlow that simplifies deep learning model implementation with an intuitive interface.
- **Image Processing Libraries:**
  - OpenCV: OpenCV (Open Source Computer Vision Library) is used for image preprocessing, including grayscale conversion and CLAHE (Contrast Limited Adaptive Histogram Equalization) enhancement.
  - NumPy: NumPy is used for handling multidimensional arrays and performing mathematical operations on image data.
  - PIL (Pillow Library): Pillow is an image processing library used for image manipulation, including resizing and format conversion.
- **Data Handling and Visualization Libraries:**
  - Pandas: Used for loading and managing datasets, structuring data for training, and performing exploratory data analysis.

- Matplotlib Seaborn: These libraries are used to visualize the dataset, training accuracy, loss curves, and confusion matrices for model evaluation.

- **Web Deployment Framework**
  - Streamlit: Streamlit is a Python-based web application framework that allows easy deployment of machine learning models with a user-friendly interface. It enables users to upload CT scan images, preprocess them, and obtain predictions from the trained deep learning model.

- **Development Environment**
  - Google Colab: Google Colaboratory (Colab) is an online cloud-based Jupyter Notebook environment that provides free access to GPUs and TPUs, making it ideal for training deep learning models.

3.8.2 System Specifications

The training and deployment of deep learning models require adequate hardware resources to ensure efficient computation and real-time inference. The system specifications define the recommended hardware configuration for model training and execution.

3.8.2.(i) **Hardware Requiremnets:**

- Processor: Intel Core i5/i7 or AMD Ryzen 5/7 (or higher)
- RAM: Minimum 8GB (16GB recommended for efficient training)
- GPU (Recommended for Deep Learning Acceleration):NVIDIA RTX 3060 / RTX 3090 / A100 / Tesla T4

- Google Colab provides access to GPUs such as Tesla K80, P100, or T4, which were used for training the model.
- Storage: At least 20GB of free space for storing datasets, model weights, and log files.

Chapter 4

RESULTS & DISCUSSION

This chapter presents the outcomes of the lung cancer classification model and provides an in-depth analysis of its performance. This section evaluates the model's effectiveness using key performance metrics such as accuracy, precision, recall, F1-score, and the confusion matrix. Additionally, visual representations like accuracy-loss curves and classification results are examined to assess the learning process and generalization capabilities of the model.

The primary goal of this study was to develop an efficient deep learning-based classification system for identifying different types of lung cancer—adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal lung tissue—from CT scan images. The model was trained using Convolutional Neural Networks (CNNs) with ConvNeXtSmall achieving the highest accuracy of 92.70%, outperforming other architectures such as ResNet50, VGG19, and CNN

Beyond training and evaluation, the model was successfully deployed using Streamlit, allowing real-time classification of lung cancer from uploaded CT scan images. The deployed application integrates image preprocessing using CLAHE, ensuring improved contrast and feature visibility before prediction. The results from real-time testing of the deployed model further validate its robustness and practical usability.

This chapter also discusses key findings, challenges, and potential improvements to enhance classification accuracy. Factors such as dataset limitations, misclassification cases, and the need for advanced ensemble techniques are considered. The discussion aims to provide insights into the strengths and weaknesses of the approach for making the system more reliable in real-world medical applications.

4.1 Performance Evaluation Metrics

Evaluating the performance of a deep learning model is essential to determine its effectiveness in real-world applications. Various metrics provide insights into the model's classification ability, ensuring that it generalizes well to unseen CT scan images. The key performance evaluation metrics used in this study include accuracy, precision, recall, F1-score, and the confusion matrix. These metrics collectively assess different aspects of the model's predictive capability, helping identify areas of strength and improvement.

4.1.1 Accuracy

Accuracy is a fundamental metric that measures the overall correctness of the model's predictions. It is defined as the ratio of correctly predicted instances (both positive and negative) to the total number of samples. In this study, the ConvNeXtSmall model achieved an accuracy of 92.70%, making it the most effective model for lung cancer classification.

The formula for accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where:

- **TP (True Positive)**: Number of correctly predicted positive cases (e.g., cancer cases correctly classified).
- **TN (True Negative)**: Number of correctly predicted negative cases (e.g., normal lung tissue correctly classified).

- **FP (False Positive)**: Number of incorrectly predicted positive cases (e.g., normal lung tissue misclassified as cancer).

- **FN (False Negative)**: Number of incorrectly predicted negative cases (e.g., a cancer case misclassified as normal).

A high accuracy value (92.70%) indicates that the model correctly classifies the majority of the images. However, accuracy alone does not provide a complete evaluation, especially in cases where the dataset is imbalanced. Therefore, additional metrics such as precision, recall, and F1-score are used for a more detailed analysis.

4.1.2 Precision, Recall, and F1-Score

These three metrics provide deeper insights into how well the model handles each class and how reliable its predictions are.

- **Precision:** Precision measures how many of the predicted positive cases were actually positive. It helps determine the model's ability to avoid false positives, which is critical in medical applications where misdiagnosing a healthy patient as having lung cancer can cause unnecessary anxiety and further testing.

  The formula for precision is:

  $$\text{Precision} = \frac{TP}{TP+FP}$$

  A high precision value suggests that the model produces fewer false alarms when classifying lung cancer.

- **Recall (Sensitivity):** Recall, also known as sensitivity, measures how many actual positive cases were correctly identified by the model. This metric is crucial in medical diagnosis since missing a cancer case (false negative) can have severe consequences.

The formula for recall is:

$$\text{Recall} = \frac{TP}{TP + FN}$$

A high recall value indicates that the model is effective at detecting lung cancer cases.

- **F1-Score:** The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation of the model's performance. It is useful in cases where there is an imbalance between positive and negative samples.

  The formula for F1-Score is:

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

  A high F1-score suggests that the model is both precise and sensitive, meaning it correctly identifies cancer cases while minimizing false positives.

4.1.3 Confusion Matrix

The confusion matrix provides a more detailed view of the model's classification performance. It breaks down the number of correct and incorrect predictions for each lung cancer type, highlighting areas where the model struggles.

4.2 Model Performance Comparison

To validate the effectiveness of the ConvNeXtSmall model, its performance was compared with other deep learning architectures tested during this project. The table below summarizes the accuracy results for different models:

Model	Accuracy
CNN	85.08%
VGG19	92.06%
ResNet50	92.00%
ConvNeXtSmall	92.70%

Table 4.1: Accuracy comparison of different models

4.3 Accuracy Curves

Analyzing the accuracy curves is essential for understanding the training dynamics of the deep learning model. These curves provide insights into how well the model is learning over successive epochs and help identify issues such as underfitting or overfitting. The accuracy curve shows how the model's classification performance improves. By evaluating these trends, we can assess whether the model has converged effectively and determine the point at which performance stabilizes.

4.3.1 CNN Accuracy Curve

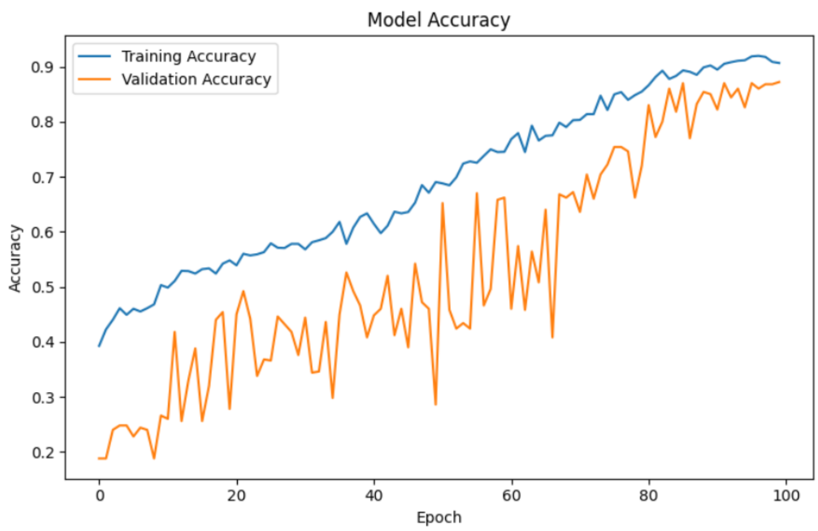

Figure 4.1: CNN Accuracy Graph

Figure 4.1 illustrate the training and validation accuracy curves for the CNN model over 100 epochs.

- **Model Accuracy:**
  - The training accuracy steadily increases, indicating that the model is learning from the training data.
  - However, the validation accuracy fluctuates significantly in the initial epochs before stabilizing in the later stages. This variation suggests that the model initially struggles with generalization but improves over time.
- **Observations and Analysis:**
  - The consistent improvement in training accuracy indicates effective learning.
  - Further hyperparameter tuning, regularization techniques, or experimenting with deeper architectures could improve the model's robustness.

4.3.2 VGG19 Accuracy Curve

Figure 4.2 illustrate the training and validation accuracy curves for the VGG19 model.

- **Model Accuracy:**
  - The training accuracy steadily increases over 35 epochs, demonstrating the model's ability to learn from the training data.
  - The validation accuracy rises consistently but exhibits minor fluctuations throughout the training process. This indicates that while the model generalizes well, there are occasional variations due to differences in the validation dataset.
- **Observations and Analysis:**

Figure 4.2: VGG19 Accuracy Graph

- The increasing trend in both training and validation accuracy suggests that the VGG19 model effectively captures important features from the input data.
- A slight gap between training and validation accuracy suggests potential overfitting, which could be mitigated using techniques such as dropout, data augmentation, or early stopping.
- The overall model performance indicates good generalization, but further optimization through hyperparameter tuning or experimenting with alternative architectures could enhance robustness and stability.

4.3.3 Resnet50 Accuracy Curve

Figure 4.3 illustrate the training and validation accuracy curves for the ResNet50 model.

- **Model Accuracy:**

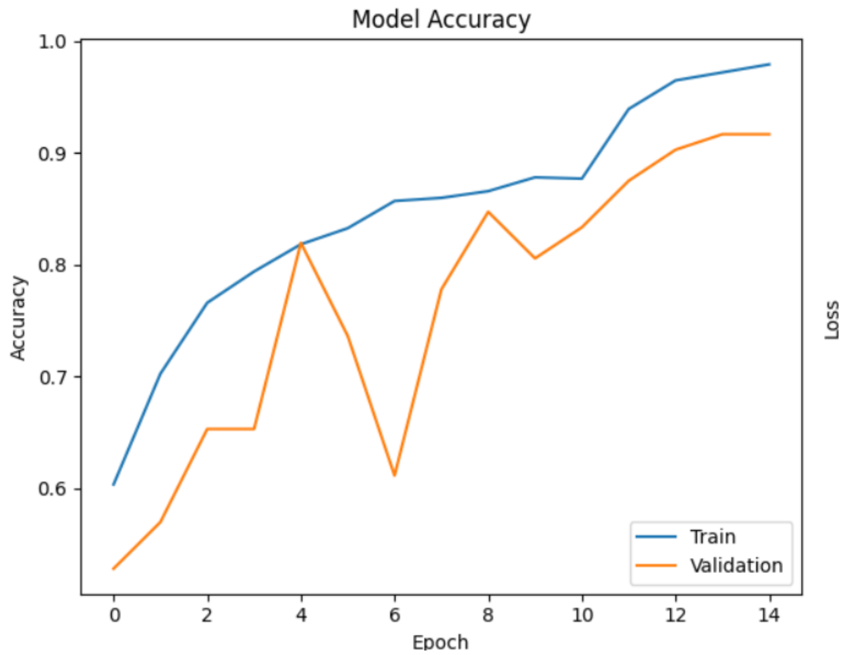

Figure 4.3: Resnet50 Accuracy Graph

- The training accuracy shows a consistent upward trend, indicating effective learning by the model over the epochs.
- The validation accuracy also improves significantly but exhibits fluctuations, particularly in the earlier epochs, before stabilizing in the later stages. This suggests that the model initially faces challenges in generalization but improves with more training.

- **Observations and Analysis:**
  - The steady increase in both training and validation accuracy confirms that the model successfully learns relevant patterns from the data.
  - However, fluctuations in validation accuracy suggest some level of overfitting, which could be addressed using techniques like dropout, regularization, or further tuning of hyperparameters.
  - The model demonstrates strong generalization capabilities, and additional fine-tuning could further enhance stability and accuracy.

4.3.4 ConvNeXtSmall Accuracy Curve

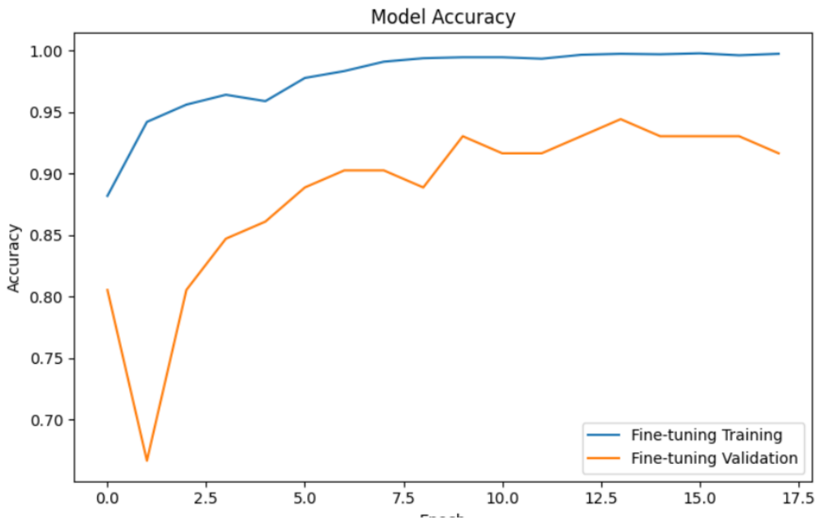

Figure 4.4: ConvNeXtSmall Accuracy Graph

Figure 4.4 illustrate the training and validation accuracy curves for the ConvNextSmall model.

- **Model Accuracy :**
  - The training accuracy increases rapidly, reaching near 100% within a few epochs, indicating that the model effectively learns patterns from the training data.
  - The validation accuracy also improves significantly, although it exhibits some fluctuations, especially in the initial epochs, before stabilizing in later stages.
- **Observations and Analysis:**
  - The rapid convergence of training accuracy suggests that the fine-tuned ConvNeXtSmall model adapts well to the dataset.
  - The validation accuracy, while high, shows some variations, indicating a potential risk of overfitting. Regularization techniques such as dropout

or weight decay could help improve generalization.

– The overall performance suggests that the model effectively captures complex patterns, and further fine-tuning of hyperparameters could further enhance stability and accuracy.

Chapter 5

CONCLUSION

In this study, a deep learning-based approach was developed for lung cancer classification using computed tomography (CT) scan images. The primary objective was to enhance the accuracy of lung cancer detection by utilizing advanced convolutional neural networks (CNNs) and transfer learning techniques. Various deep learning architectures, including CNN, VGG19, ResNet50, and ConvNeXtSmall, were implemented and evaluated to determine the most effective model for this classification task.

The results indicate that ConvNeXtSmall achieved the highest classification accuracy, outperforming other architectures in terms of generalization and robustness. The application of image preprocessing techniques, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), significantly enhanced the quality of CT scan images, improving feature extraction and overall model performance. Furthermore, data augmentation strategies were employed to mitigate class imbalance and enhance the model's ability to generalize across diverse lung cancer cases.

Despite these promising results, several challenges were encountered during the study. One of the primary limitations was the restricted dataset size, which may have affected the model's ability to generalize effectively. Additionally, the computational complexity of deep learning models, particularly ConvNeXtSmall, required substantial training time and GPU resources. Another challenge was class imbalance, which had an impact on model performance, necessitating augmentation techniques and careful dataset partitioning.

To further enhance the system, several improvements can be explored. The integration of ensemble learning techniques by combining multiple deep learning models could potentially improve classification accuracy. Expanding the dataset by incorporating multi-source CT scans would enhance model generalization across a wider range of cases. Additionally, adopting explainable AI (XAI) techniques could provide greater interpretability of the model's predictions, making it more useful for medical professionals.

This study demonstrates the potential of deep learning in automating lung cancer classification, thereby assisting radiologists in early diagnosis and treatment planning. With further optimization and access to larger datasets, deep learning models can play a crucial role in advancing medical imaging-based disease detection and improving patient outcomes.

5.1 Future Scopes

The lung cancer classification system using deep learning presents a strong foundation for automated cancer detection. However, there are several areas where further advancements can be made to enhance its performance, reliability, and practical applicability. The following future scopes highlight key areas for improvement and potential research directions:

- **Integration of Ensemble Learning:** Combining multiple deep learning models, such as VGG19, ResNet50 and ConvNeXtSmall, using ensemble techniques can significantly improve classification accuracy and robustness. Ensemble learning works by aggregating the predictions of multiple models, thereby reducing biases and enhancing the model's ability to generalize across diverse lung cancer cases. This approach helps mitigate the weaknesses of individual models and leads to a more reliable classification system.

- **Expansion of Dataset and Multi-Center Validation:** A key factor in improving the performance of the lung cancer classification model is the expansion of the dataset. Increasing the size and diversity of the dataset by incorporating CT scans from multiple medical institutions can enhance the model's generalization ability. A larger and more varied dataset can help address class imbalance issues, ensuring that the model performs well across different patient populations. Additionally, multi-center validation ensures that the model is not biased toward a specific dataset and can generalize effectively to real-world clinical scenarios.

- **Integration of Explainable AI (XAI) Techniques:** One of the challenges in deep learning-based medical applications is the lack of interpretability. Implementing Explainable AI (XAI) techniques, such as Grad-CAM (Gradient-weighted Class Activation Mapping) and SHAP (SHapley Additive exPlanations), can improve the transparency of the model's predictions. These techniques allow medical professionals to understand why the model classified a CT scan as cancerous or non-cancerous, making it more trustworthy for clinical use. This interpretability is essential for building confidence among radiologists and facilitating the adoption of AI-assisted diagnosis.

- **Development of a Clinical Decision Support System (CDSS):** The lung cancer classification model can be further developed into a Clinical Decision Support System (CDSS) that assists medical professionals in diagnosing, monitoring, and planning treatments for lung cancer patients. Integrating this system with hospital databases and electronic health records (EHRs) can enable real-time analysis of patient data, improving decision-making efficiency. A CDSS would act as a second opinion for doctors, helping them detect lung cancer at an early stage and recommending appropriate treatment plans.

- **Real-Time Detection and 3D CT Image Processing:** The current model primarily focuses on 2D CT scan images, but expanding it to process 3D CT scans can significantly improve diagnostic accuracy. 3D image processing allows for a more comprehensive analysis of lung tumors, capturing details that might be missed in 2D slices. Additionally, integrating real-time detection systems into medical imaging machines can provide instant feedback to radiologists, making the diagnostic process faster and more efficient.

- **Fine-Tuning with Transfer Learning and Advanced Architectures:** Further improvements can be made by exploring more advanced CNN architectures such as Vision Transformers (ViTs), Swin Transformers, or EfficientNetV2. These modern architectures have shown superior performance in image classification tasks and could potentially enhance the model's accuracy. Additionally, fine-tuning pretrained models on domain-specific lung cancer datasets can further improve performance by leveraging transfer learning, enabling the model to learn more representative features from medical images.

- **Integration with AI-Assisted Radiology Workflows:** AI can play a vital role in radiology workflows by assisting radiologists in prioritizing cases based on the severity of lung cancer. The lung cancer classification model can be integrated into AI-driven radiology systems, helping automate the screening process and ensuring that critical cases are flagged for immediate review. This automation can help optimize diagnostic processes, reduce the workload on radiologists, and improve the efficiency of lung cancer diagnosis.

By implementing these future advancements, the lung cancer classification system can evolve into a highly accurate, reliable, and clinically applicable AI-driven diagnostic tool, ultimately contributing to early detection, better patient outcomes, and advancements in AI-powered medical diagnostics.

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APPENDIX

6.1 Screenshots

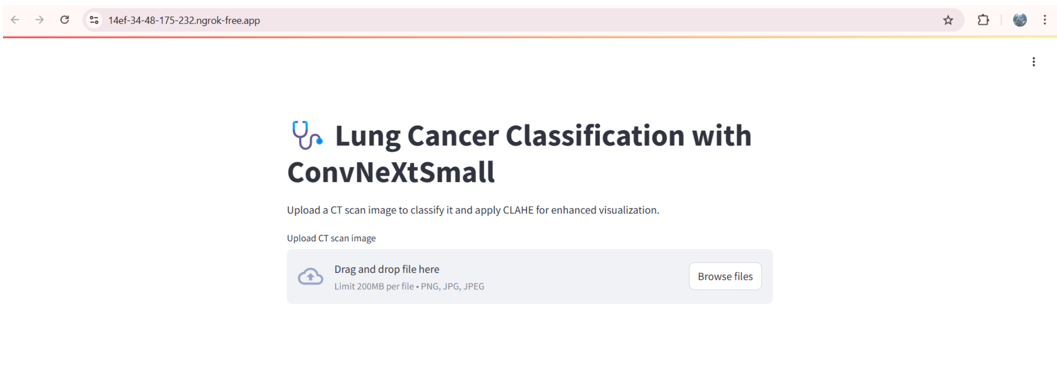

Figure 6.1.1: User Interface

Figure 6.1.2: Image enhancement and Final Prediction