# Lung Cancer Detection from CT Scans Using Deep Learning

# Part 1: Introduction

Lung cancer is one of the leading causes of cancer-related deaths worldwide. Early and accurate detection of malignant growths in the lungs significantly improves patient survival rates. Traditionally, radiologists inspect CT scans manually, a process that can be time-consuming and prone to subjectivity.

Recent advancements in artificial intelligence, especially deep learning, have shown great promise in automating medical image analysis. This project focuses on leveraging a deep learning model to classify lung CT scan images into three categories: Benign, Malignant, and Normal, thereby assisting clinicians in early diagnosis and treatment planning.

# Part 2: Problem Statement

Manual interpretation of lung CT scans presents several challenges:  
- High volume of scans and complexity of visual features  
- Inter-observer variability in assessments  
- Difficulty in detecting small nodules or early signs of malignancy

Objectives:  
- Develop an automated image classification model to detect lung cancer.  
- Classify CT scans into Benign, Malignant, or Normal categories.  
- Provide a web-based interface for clinicians and users to upload scans and receive predictions with confidence levels.  
- Improve diagnostic support in resource-limited clinical settings.

# Part 3: Dataset Overview

For this project, a curated dataset of lung CT scan images was used. The dataset includes labeled examples representing:  
- Normal lungs with no signs of abnormalities.  
- Benign tumors (non-cancerous growths).  
- Malignant tumors (cancerous growths).

Image Specifications:  
- Format: JPEG/PNG  
- Color Mode: RGB  
- Input Size: Resized to 256×256 pixels during preprocessing  
- Labels: Provided by radiology experts

The dataset was split into training, validation, and test sets to evaluate model generalizability.

# Part 4: Preprocessing Pipeline

To ensure consistent model performance and data quality, several preprocessing steps were applied:

1. Image Resizing:  
 - All images were resized to 256×256 pixels to match the model's input requirements.

2. Normalization:  
 - Pixel values were scaled to the [0,1] range using min-max normalization.

3. Color Channel Standardization:  
 - All images were converted to RGB format for uniformity.

4. Data Augmentation (optional):  
 - Techniques like flipping, rotation, and brightness adjustments can be applied to improve generalization.

# Part 5: Model Architecture

A convolutional neural network (CNN) model was used for image classification. The model structure includes:

- Input Layer: Accepts 256×256 RGB images.  
- Convolutional Layers: Extract spatial features using filters.  
- Pooling Layers: Reduce spatial dimensions and control overfitting.  
- Fully Connected Layers: Classify features into the desired output classes.  
- Softmax Output Layer: Provides probability distribution over the 3 classes.

The model was implemented using TensorFlow/Keras and trained from scratch or using transfer learning from a pre-trained backbone (e.g., MobileNet, ResNet).

# Part 6: Training Setup

The training process was conducted on a local machine with GPU acceleration (if available).

Configuration Details:  
- Input Size: (256, 256, 3)  
- Loss Function: Categorical Crossentropy  
- Optimizer: Adam with a learning rate of 0.001  
- Batch Size: 32  
- Epochs: 20–30  
- Validation Split: 20% of training data

Model performance was monitored through training/validation accuracy and loss curves.

# Part 7: Results & Evaluation

The model achieved high accuracy in classifying lung CT scans on the test dataset.

Metrics Used:  
- Accuracy  
- Precision, Recall, and F1-score per class  
- Confusion Matrix

Example Output:  
For a given image, the model predicts:  
- Class: Malignant  
- Confidence: 94.78%

The results showed that the model is capable of distinguishing between malignant, benign, and normal lung conditions with high reliability.

# Part 8: Visualization & Insights

The web app built using Streamlit allows users to:

- Upload CT scan images.  
- View the image alongside the predicted class.  
- See the prediction confidence level.  
- Get real-time results via the integrated model.

This visualization enhances trust and interpretability for end-users and clinicians.

# Part 9: Key Takeaways

- A deep learning classifier can accurately distinguish between different lung conditions using CT scans.  
- Image preprocessing and normalization are critical for model performance.  
- The application of Streamlit provides an accessible interface for medical image diagnosis.  
- Future integration with hospital PACS systems could make such tools widely available in clinics.

# Part 10: Future Work

Improvements Proposed:  
- Include Grad-CAM visualizations to highlight regions influencing the prediction.  
- Incorporate 3D CT scan slices for volumetric analysis.  
- Use larger and more diverse datasets to improve robustness.  
- Deploy the model to the cloud for broader accessibility.

Evaluation Enhancements:  
- Apply ROC-AUC metrics for more detailed performance tracking.  
- Conduct cross-validation across patient groups.