Project Document: Lung Segmentation from Chest X-ray Images using U-Net

# Abstract

This project implements a deep learning-based U-Net model for segmenting lungs from chest X-ray images. Using Python and TensorFlow in a Google Colab environment, this work aims to automate the extraction of lung regions to aid in medical diagnosis. This document provides a detailed explanation of the code and methodology used.

# 1. Introduction

Lung segmentation is a crucial step in analyzing chest X-ray images, which can assist in detecting various pulmonary diseases. Manual segmentation is labor-intensive and error-prone, thus deep learning techniques like U-Net are used for precise and automated segmentation.

# 2. Dataset Description

The dataset typically contains grayscale chest X-ray images along with corresponding binary masks that highlight the lung regions. These images and masks are preprocessed and resized for input into the neural network.

# 3. Code Explanation

\*\*Step 1: Import Required Libraries\*\*

Libraries such as NumPy, pandas, matplotlib, OpenCV, TensorFlow, and Keras are imported to support data manipulation, image processing, model building, and visualization.

\*\*Step 2: Load and Preprocess the Data\*\*

Images and their corresponding masks are loaded from directories. The data is resized to a fixed dimension (e.g., 128x128 or 256x256) and normalized.  
Preprocessing also includes reshaping and splitting into training and validation sets.

\*\*Step 3: Define the U-Net Model\*\*

The U-Net model is a convolutional neural network with an encoder-decoder structure:  
- Encoder path consists of Conv2D and MaxPooling layers to extract features  
- Decoder path includes Conv2DTranspose or UpSampling layers to reconstruct image resolution  
- Skip connections are used to combine encoder and decoder features  
The output layer uses a sigmoid activation function for binary mask prediction.

\*\*Step 4: Compile the Model\*\*

The model is compiled using 'binary\_crossentropy' as the loss function and 'adam' optimizer. IoU (Intersection over Union) or Dice Coefficient may be used as additional evaluation metrics.

\*\*Step 5: Train the Model\*\*

The model is trained using the fit() function with training and validation datasets. Epochs and batch size are tuned to improve accuracy. Callbacks such as ModelCheckpoint and EarlyStopping are used to save the best model and prevent overfitting.

\*\*Step 6: Model Evaluation and Prediction\*\*

The model is evaluated on the validation or test set. Metrics such as accuracy and loss are plotted using matplotlib. Predicted masks are overlaid on the original images to visually inspect performance.

# 4. Results

The U-Net model demonstrates high performance in segmenting lung areas from chest X-rays. Visualization of predicted masks shows accurate boundary detection and minimal false positives.

# 5. Conclusion

U-Net is an effective architecture for medical image segmentation tasks like lung segmentation. This project successfully implements and explains a full segmentation pipeline using chest X-ray images.

# 6. References

[1] U-Net: Convolutional Networks for Biomedical Image Segmentation (Ronneberger et al.)  
[2] TensorFlow/Keras Documentation - https://www.tensorflow.org/  
[3] Chest X-ray Segmentation Dataset - Available on Kaggle