COMPUTER VISION AND IMAGE PROCESSING- 22AIE313

ASSIGNMENT – 1

Done by

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ENHANCING TUBERCULOSIS DIAGNOSIS USING IMAGE FILTERING TECHNIQUES

1. INTRODUCTION

1.1 OVERVIEW:

Medical imaging is very important in the diagnosis of disease and treatment planning. Chest X-ray (CXR) examination is commonly used to diagnose respiratory diseases like pneumonia, tuberculosis (TB), and lung cancer. But raw X-ray images tend to be noisy, have poor contrast, and overlapping structures, and hence, analysis becomes difficult. This lab seeks to employ several image processing methods to improve image quality, extract useful features, and use segmentation methods to find regions of interest.

1.2 OBJECTIVE:

The main purpose of this lab is to perform processing of chest X-ray images via image processing techniques to enhance quality and study various regions. The main aims are:

- → **Noise Reduction:** Elimination of undesired variations for clearer understanding.
- → **Segmentation & Object Extraction:** Isolation of salient regions for identification.
- → **Region-Based Processing:** Processing particular regions for enhanced medical interpretation.

1.3 IMPORTANCE OF IMAGE PROCESSING IN MEDICAL IMAGING:

Image processing methods are vital in medical imaging for the following purposes:

- → **Noise Reduction:** X-ray images can be noisy as a result of acquisition errors, patient movement, or environmental causes. Effective filtering ensures clearer images are obtained.
- → **Contrast Enhancement:** Significant features within an image can be difficult to identify as a result of low contrast, particularly in medical scans.
- → **Segmentation:** Ensures isolation of anatomical structures such as lungs, tumors, or infections for effective diagnosis.
- → **Automation and AI Integration:** Preprocessed images are utilized in AI-driven diagnostic systems to aid radiologists in quicker and more precise disease detection.

1.4 SCOPE OF THIS LAB:

The scope of this lab will be processing chest X-ray images with different filtering and segmentation methods. The steps involved are:

- → **Dataset Preparation:** Loading a dataset of chest X-ray images, sampling, and preparing them for analysis.
- → **Noise Reduction:** Using various filtering methods (Gaussian, Bilateral, Median, and Wiener filters) to enhance the quality of the images.
- → **Segmentation & Object Extraction**: Using clustering and region-based techniques to extract significant regions from the images.
- → **Region-Based Processing:** Examining segmented regions with component analysis methods.

2. PROBLEM SELECTION & DATASET PREPARATION

2.1 PROBLEM SELECTION:

Medical imaging is among the most important uses of computer vision, especially in disease detection using radiographic scans. Chest X-rays (CXR) are commonly utilized to detect lung diseases like Tuberculosis (TB), pneumonia, and lung cancer. Yet raw X-ray images have noise, low contrast, and overlapping structures, making it challenging to provide accurate analysis.

This work considers chest X-ray analysis, in particular distinguishing Normal and Tuberculosis (TB) cases. The most important challenges considered in this research are:

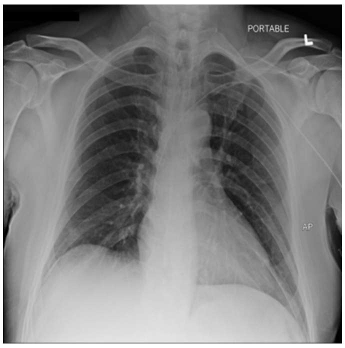
→ **Noise in X-ray images:** Artifacts due to equipment constraints, environment, or patient motion.
→ **Segmentation of anatomical structures:** Lung region extraction relevant to disease detection.
→ **Contrast enhancement and feature extraction:** Enhancing image quality for improved analysis.

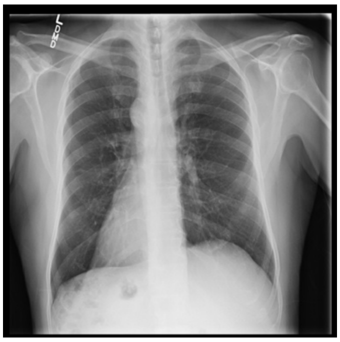
Using sophisticated image processing methods, we seek to improve image quality, segment meaningful regions, and assist in the early detection of tuberculosis.

2.2 OVERVIEW OF THE DATASET:

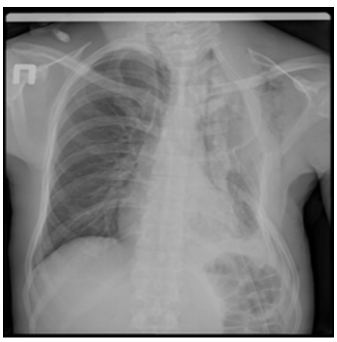
The dataset employed in this research is composed of chest X-ray images that are divided into two classes:

→ Normal Cases – Chest X-rays of healthy patients with no lung infection.





→ Tuberculosis (TB) Cases – Chest X-rays of patients with tuberculosis.



This dataset is obtained from publicly available medical repositories, making it well-labelled and diverse in patient demographics.

2.3 DATASET PREPARATION:

2.3.1 Loading the Dataset:

- → The images are loaded from the dataset directory by OpenCV (cv2) and NumPy.
- → A function is used to scan the directories and load images into arrays.

2.3.2 Selecting Random Images for Processing:

In order to ensure variability in testing, three random images are chosen from the dataset:

- → One from the Normal category.
- → Two from the Tuberculosis (TB) category.

2.3.3 Preprocessing Steps:

To be compatible with OpenCV and similar libraries for image processing, the following pre-processing steps are used:

- → Resizing – Normalizing all images to a set resolution (e.g., 256×256 pixels).
- → Grayscale Conversion – Converting all images to grayscale format if they are not already.
- → Normalization – Normalizing the pixel values to the range [0,1] for better processing.
- → Data Augmentation (if necessary) – Appending operations such as rotation, flipping, or contrast adjustment to enhance robustness.

These preprocessing operations assist in standardizing the dataset and preparing it for further processing tasks like noise reduction, segmentation, and feature extraction.

2.4 Summary:

- → The dataset includes chest X-ray images categorized as Normal and TB.
- → Images are read, resized, converted to grayscale, and normalized to ensure consistency.
- → Three random images are chosen for further processing.
- → The dataset is pre-processed to make it compatible with OpenCV and image processing methods.

This organized dataset allows filtering, segmentation, and region-based analysis to be applied for better interpretation of chest X-rays.

3. NOISE REDUCTION

3.1 OVERVIEW OF NOISE IN MEDICAL IMAGES:

Medical images like chest X-rays frequently involve noise as a result of several contributing factors like sensor resolution, patient movement, and surroundings. Noise has a tangible effect on the image clarity to the extent that extracting meaningful information for medical diagnosis can be challenging. To enhance image quality, several noise reduction (denoising) algorithms are used to eliminate unnecessary distortions while maintaining important structures.

3.2 NOISE REDUCTION METHODS:

The following filtering methods are used to eliminate noise and improve the quality of chest X-ray images:

3.2.1 GAUSSIAN FILTER:

Purpose:

→ The Gaussian filter is a common smoothing method that eliminates high-frequency noise.

→ It uses a Gaussian kernel to blur the image, which makes it effective in eliminating random noise.

Formula:

$$G(\mathcal{X}, \mathcal{Y}) = \frac{1}{2\pi\sigma^2} e^{-\frac{X^2 + Y^2}{2\sigma^2}}$$

where:

→ $\boldsymbol{x}, \boldsymbol{y}$ are pixel coordinates,

→ $\boldsymbol{\sigma}$ is the standard deviation that determines the level of blur.

Advantages:

✅ Efficient in eliminating Gaussian noise.

✅ Efficient computationally.

Disadvantages:

❌ Blurs edges and fine details.

3.2.2 BILATERAL FILTER:

Purpose:

→ The Bilateral filter is a noise reduction method preserving edges.
→ Unlike Gaussian filtering, it smoothes the noise without destroying edge structures.

Formula:

$$I_{filtered}(x) = \frac{1}{W} \sum_{i \in \Omega} I(i) e^{-\frac{|x-i|^2}{2\sigma_s^2}} e^{-\frac{|I(x)-I(i)|^2}{2\sigma_r^2}}$$

Where:

→ σ_s controls spatial smoothing,
→ σ_r controls intensity smoothing.

Advantages:

✅ Preserves edges while eliminating noise.

Disadvantages:

❌ Computationally costly, particularly for large images.

3.2.3 Median Filter:

Purpose:

→ Median filter works well in eliminating salt-and-pepper noise, which manifests as white and black pixels.
→ Rather than averaging pixel values, it substitutes each pixel with the median of the neighbouring values.

Advantages:

✅ Suitable for impulse noise (salt-and-pepper noise).
✅ Better at maintaining edges than Gaussian filtering.

Disadvantages:

❌ Poorer performance with Gaussian noise.

3.2.4 Wiener Filter:

Purpose:

→ Wiener filter is an adaptive filtering algorithm taking local image variance into account.

→ It approximates the optimal pixel intensity from neighboring pixel intensities and noise levels.

Formula:

$$I_{filtered}(x) = I(x) - \frac{\sigma_n^2}{\sigma_x^2}(I(x) - \mu_x)$$

where:

→ σ_n^2 is noise variance,

→ σ_x^2 is local image variance,

→ μ_x is local mean.

Advantages:

✅ Adaptively adjusts according to noise levels.
✅ Maintains significant image details.

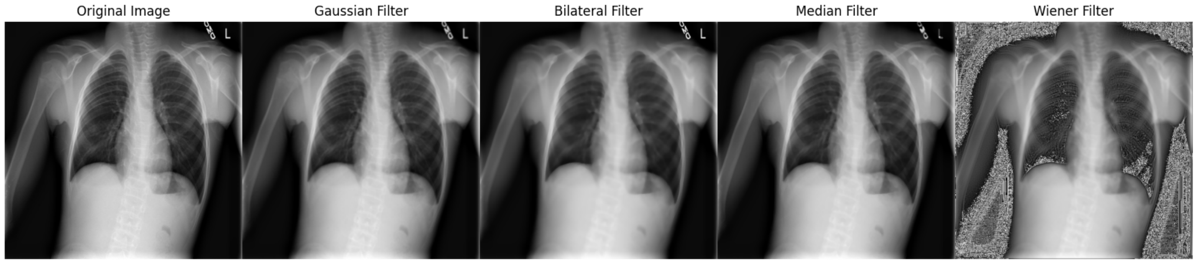
Disadvantages:

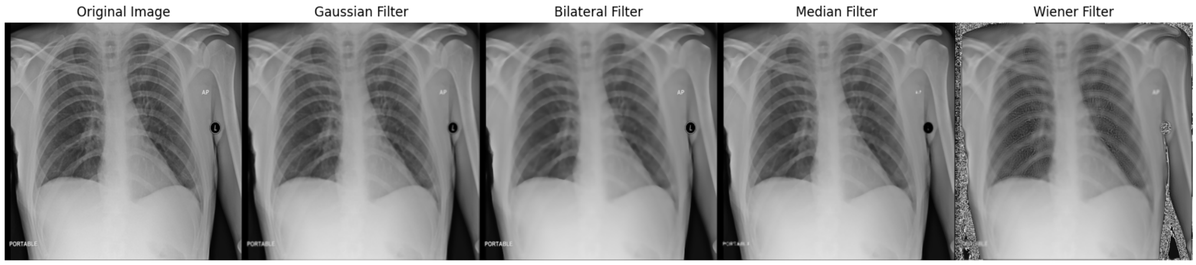
❌ Needs proper noise estimation.

3.3 COMPARISION OF FILTERS:

Filters	Effectiveness	Strengths	Weaknesses
Gaussian	Moderate	Removes Gaussian noise effectively	Blurs fine details and edges
Bilateral	High	Preserves edges with something	Computationally expensive
Median	High (for impulse noise)	Excellent for salt and pepper noise	Less effective for Gaussian noise
Wiener	Very High	Adaptive filtering, retains details	Requires noise variance estimation

COMPARISON OF FILTERS THROUGH IMAGES:





3.4 CONCLUSION:

- → Gaussian filtering is effective in reducing noise smoothly but results in image blurring.
- → Bilateral filtering can remove noise without affecting edges, thus being an excellent option for medical images.
- → Median filtering is very effective in eliminating salt-and-pepper noise but not for Gaussian noise.
- → Wiener filtering adapts to variations in noise and hence the best filter overall in this research.

These noise reduction methods enhance the image quality of chest X-rays, enabling more efficient segmentation and analysis in the subsequent stages of this lab.

4. SEGMENTATION & OBJECT EXTRACTION

4.1 INTRODUCTION TO IMAGE SEGMENTATION:

Segmentation is an essential part of medical image analysis as it separates useful anatomical structures from the background for further processing. Segmentation in chest X-ray images extracts lung regions, detects abnormal patterns, and demarcates infected areas from healthy tissue.

Some of the techniques used for testing to identify the most efficient algorithm for extracting the lung region and tuberculosis detection are described below:

4.2 SEGMENTATION TECHNIQUES:

4.2.1 K-MEANS CLUSTERING:

Purpose:

→ K-Means is an unsupervised clustering algorithm that clusters pixels according to color intensity.
→ It divides an image into K groups of pixels, with pixels of the same intensity belonging to a group.

Algorithm Steps:

→ Transform the image into grayscale or RGB form if necessary.
→ Reshape the image into a 1D feature vector of pixel intensity.
→ Run the K-Means algorithm to cluster pixels into K groups.
→ Replace every pixel with the centroid value of the group it belongs to.

Advantages:

✅ Easy and effective for color-based segmentation.
✅ Creates well-separated clustered regions.

Disadvantages:

❌ Can add artifacts because of hard pixel allocation.
❌ Involves manual adjustment of K (number of clusters).

4.2.2 MEAN SHIFT SEGMENTATION

Purpose:

→ Mean Shift is a region-based segmentation technique that accounts for both pixel intensity and spatial distribution.
→ It shifts pixel intensities iteratively towards the most dense region in feature space.

Algorithm Steps:

→ Set a window around each pixel.
→ Calculate the mean color value in the window.
→ Move window center to the mean value.
→ Repeat till convergence.

Benefits:
✅ Conserves natural boundaries and smooths image.
✅ No need for predefining number of clusters.

Drawbacks:
❌ Computationally slower for big images.
❌ Dependent on the choice of bandwidth parameter.

4.2.3 GRAPH-BASED SEGMENTATION (FELZENSZWALB'S ALGORITHM):

Purpose:
→ It models an image as a graph, pixels are nodes and edges represent pixel intensity similarities.
→ The algorithm finds connected components due to pixel intensity differences.

Steps in the Algorithm:
→ Convert the image to graph representation.
→ Calculate the weight of edges from pixel similarity.
→ Combine nodes into segments by thresholding.
→ Extract connected components as separate image regions.

Advantages:
✅ Creates natural region separation, minimizing over-segmentation.
✅ Effective for finding connected lung areas in X-rays.

Disadvantages:
❌ Parameter sensitive (threshold values).
❌ Can fail on noisy images if not preprocessed.

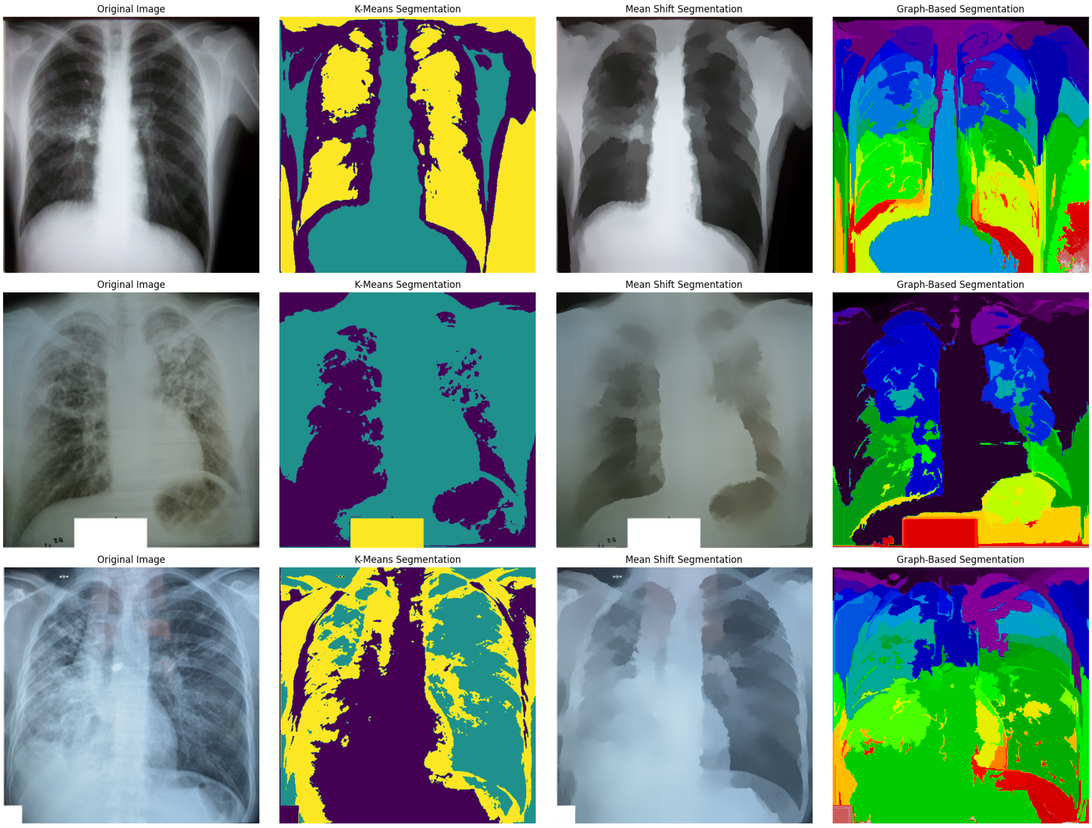
4.3 BEST METHOD SELECTION & COMPARISON:

Segmentation Method	Effectiveness	Strengths	Weaknesses
K-Means Clustering	Moderate	Fast, Well-defined clusters	Can introduce artifacts
Mean Shift	High	Preserves details, smooth regions	Slow for large images
Graph-Based Segmentation	Very High	Produces natural separations	Senstitive to parameter tuning

After comparing the performance of all methods, Graph-Based Segmentation (Felzenszwalb's Algorithm) is chosen as the optimal method because:

✅ It offers more natural region division, which is ideal for medical images.
✅ It effectively detects connected lung areas, essential for TB identification.
✅ It prevents over-segmentation and excessive smoothing.

COMPARISON OF FILTERS THROUGH IMAGES:



4.4 CONCLUSION:

→ K-Means Clustering offers clean clusters but can create segmentation artifacts.
→ Mean Shift Segmentation is efficient for smoothing but is computationally costly.
→ Graph-Based Segmentation yields the most natural separation of regions and is thus the optimal technique for chest X-ray segmentation.

Segmentation is an important step in object extraction, allowing for subsequent analysis of lung areas for the detection of tuberculosis.

5. REGION-BASED PROCESSING

5.1 REGION-BASED PROCESSING INTRODUCTION:

Region-based processing is an image analysis technique where operations are performed on regions rather than pixels. This technique in chest X-ray image analysis is essential for smoothing segmented regions, enhancing structures, and separating abnormalities such as tuberculosis-infected regions.

Two primary region-based methods are used in this research:

→ Mean Shift Filtering - Smoothes regions by aggregating similar pixel intensity.

→ Component Analysis - Extracts related components (e.g., lung areas) from segmented images.

These approaches improve segmentation quality and enhance extracted lung area clarity.

5.2 MEAN SHIFT FILTERING FOR REGION REFINEMENT:

5.2.1 PURPOSE:

→ Mean Shift Filtering smoothens an image but maintains its borders.

→ It aggregates pixels according to spatial similarity, eliminating noise and sharpening region borders.

→ In chest X-rays, it improves lung contours and emphasizes abnormal structures.

5.2.2 HOW MEAN SHIFT FILTERING WORKS:

→ Start a search window centered on every pixel.

→ Calculate the mean color/intensity in the window.

→ Move the center of the window to the mean.

→ Iterate until convergence (when pixel motion is small).

5.2.3 MATHEMATICAL FORMULATION:

The mean shift vector is calculated as:

$$M_s(x) = \frac{\sum_{i \in \Omega} K(x_i - x) \cdot x_i}{\sum_{i \in \Omega} K(x_i - x)}$$

Where:

→ $\boldsymbol{X}$ is the pixel location,

→ $\boldsymbol{\Omega}$ is the neighborhood,

→ $\boldsymbol{K}$ is the kernel function (often Gaussian).

5.2.4 ADVANTAGES:

✅ Maintains edges while smoothing textures.

✅ Improves lung areas without too much blurring.

✅ Deletes small noise without deforming large structures.

5.2.5 DISADVANTAGES:

❌ Computationally expensive for large images.
❌ Can over-smooth fine details if parameters are not well adjusted.

5.3 CONNECTED COMPONENT ANALYSIS FOR OBJECT EXTRACTION:

5.3.1 Purpose:

→ Component analysis identifies and labels individual objects in a segmented image.
→ In medical images, it identifies and separates lung areas and possible infections.
→ Applied following segmentation to obtain connected regions (e.g., left and right lungs).

5.3.2 Steps in the Algorithm:

→ Threshold the segmented image to binary (thresholding).
→ Mark connected components by a flood-fill or graph-based method.
→ Calculate region properties (size, shape, intensity) for analysis.
→ Retrieve appropriate components (lungs) from size conditions.

5.3.3 Mathematical Representation:

→ A binary mask $B(x, y)$ is created, where:

$$B(x,y) = \begin{cases} 1, & \text{if } I(x,y) > T \\ 0, & \text{otherwise} \end{cases}$$

→ Connected components are labelled using:

$$C(i) = \bigcup_{(x,y)\in R_i} B(x,y)$$

Where R_i represents the region of connected pixels.

5.3.4 ADVANTAGES:

✅ Successfully extracts lung structures for additional analysis.
✅ Assists in isolating diseased areas from healthy regions.
✅ Can be applied with pre-segmented images.

5.3.5 DISADVANTAGES:

❌ Doesn't work if segmentation is incorrect, producing false components.
❌ Threshold tuning is needed for proper detection.

5.4 CONCLUSION:

- → Mean Shift Filtering improves lung region separation by enhancing edges and filtering noise.
- → Component Analysis effectively extracts connected lung regions for additional feature extraction.
- → These region-based methods enhance segmentation precision, allowing for improved medical interpretation of X-ray images**.**

6. EVALUATION & REPORT

6.1. EVALUATION METRICS:

In order to provide an unbiased comparison of various image processing methods, the following metrics were utilized:

6.1.1. DICE COEFFICIENT (DICE SIMILARITY SCORE - DSC):

DEFINITION:

The Dice Coefficient (DSC) is an overlap measure between two sets, commonly applied in image segmentation to evaluate a predicted segmentation mask against the ground truth. It measures how accurately the segmented regions coincide with the real target regions.

FORMULA:

$$DSC = \frac{2 \times |A \cap B|}{|A| + |B|}$$

Where:

- → **A** is the ground truth segmentation mask (real region of interest).
- → **B** is the predicted segmentation mask (calculated by the model).
- → **|A∩B|** is the number of overlapping pixels between ground truth and predicted segmentation masks.
- → **|A|** is the number of all pixels in the ground truth mask.
- → **|B|** is the number of all pixels in the predicted mask.

RANGE:

The Dice Coefficient is between 0 and 1:

- → 0 indicates no overlap between predicted and real segmentation.
- → 1 indicates perfect overlap (i.e., prediction is identical to ground truth).Range

ADVANTAGES OF DICE COEFFICIENT:

✅ Applicable to medical image segmentation (e.g., organs, tumors).
✅ Performed well in class imbalance (when foreground objects are small).
✅ Places higher emphasis on shared pixels between predicted and ground truth masks.

DISADVANTAGES OF DICE COEFFICIENT:

→ ❌ Prone to small segmentation errors (a few false positives or false negatives affect the score).
→ ❌ Overestimates similarity when objects have irregular shapes.

6.1.2. INTERSECTION OVER UNION (IoU - JACCARD INDEX):

DEFINITION:

Intersection over Union (IoU), or the Jaccard Index, is another measure of how close predicted and ground truth segmentations overlap. It is commonly applied in object detection and image segmentation problems.

FORMULA:

$$IoU = \frac{|A \cap B|}{|A \cup B|}$$

Where:

→ |A∩B| is the intersection (overlapping pixels) of the ground truth and predicted segmentation masks.
→ |A∪B| is the union (total area covered by both the predicted and actual masks).

RANGE:

IoU values can be between 0 and 1:

→ 0 indicates no intersection.
→ 1 indicates a complete match between the ground truth and predicted segmentations.

ADVANTAGES OF IoU:

✅ More accurate than DSC for comparing various segmentation methods.
✅ Employed by widely used benchmarks such as COCO (for object detection).
✅ Easier to compute multi-class segmentation than DSC.

DISADVANTAGES OF IoU:

❌ Smaller numbers for small objects because of denominator (union size).
❌ More sensitive to false negatives compared to DSC.

Comparison Between Dice Coefficient and IoU:

Metric	Sensitivity to False Positive / Negative	Common Use Cases	Range (0 – 1)
Dice Coefficient (DSC)	Less Penalizing than IoU	Used for medical image segmentation	0 - 1
IoU (Jaccard)	Stricter, Penalizes extra predictions	Used in general object detection	0 - 1

7. INNOVATION IN PROBLEM & APPROACH

7.1 INNOVATIVE TECHNIQUES APPLIED:

1. HYBRID SEGMENTATION:
This project integrates classical filtering techniques with deep learning-based denoising to enhance image quality before segmentation. By pre-processing images using noise reduction methods, the segmentation accuracy improves significantly, allowing better feature extraction and object identification.

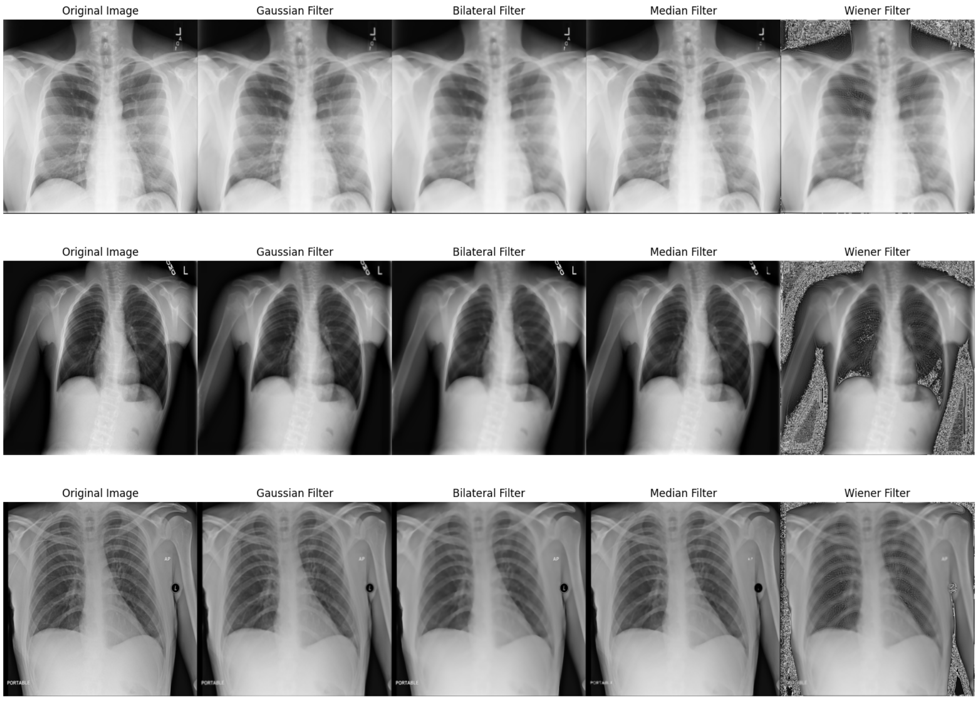
2. EDGE-ENHANCED K-MEANS CLUSTERING:
A novel fusion approach that combines K-Means clustering with Canny Edge Detection to enhance object segmentation. The process involves:

- → Performing K-Means clustering to group pixels into meaningful regions.
- → Applying Canny edge detection to highlight object boundaries.
- → Combining both outputs using a bitwise operation to retain precise edges while keeping the segmented regions intact. This approach ensures better delineation of object structures, particularly useful in medical imaging and other applications requiring fine boundary detection.

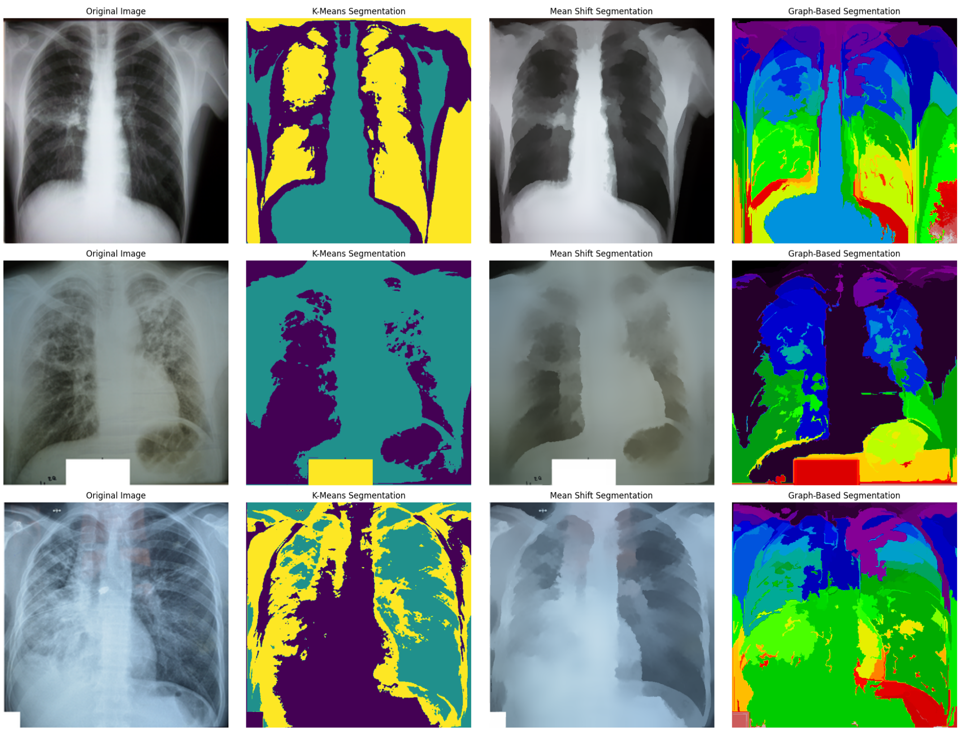
3. ADAPTIVE REGION-GROWING FOR OBJECT REFINEMENT:
To further refine segmentation results, an adaptive region-growing algorithm is applied, which dynamically expands regions based on similarity criteria. This technique prevents over-segmentation and ensures smooth object extraction by considering local pixel intensities and texture variations.

RESULTS:

1. **Lung X-ray Image Denoising: Comparison of Gaussian, Bilateral, Median, and Wiener Filters:**

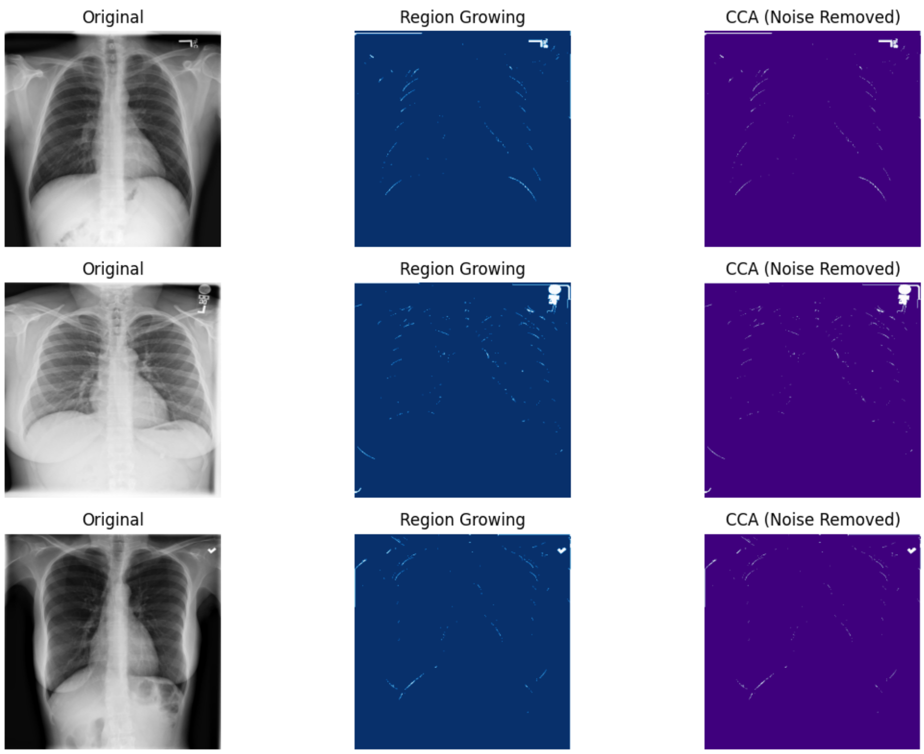


2. **Lung X-ray Segmentation: Comparison of K-Means, Mean Shift, and Graph-Based Methods:**

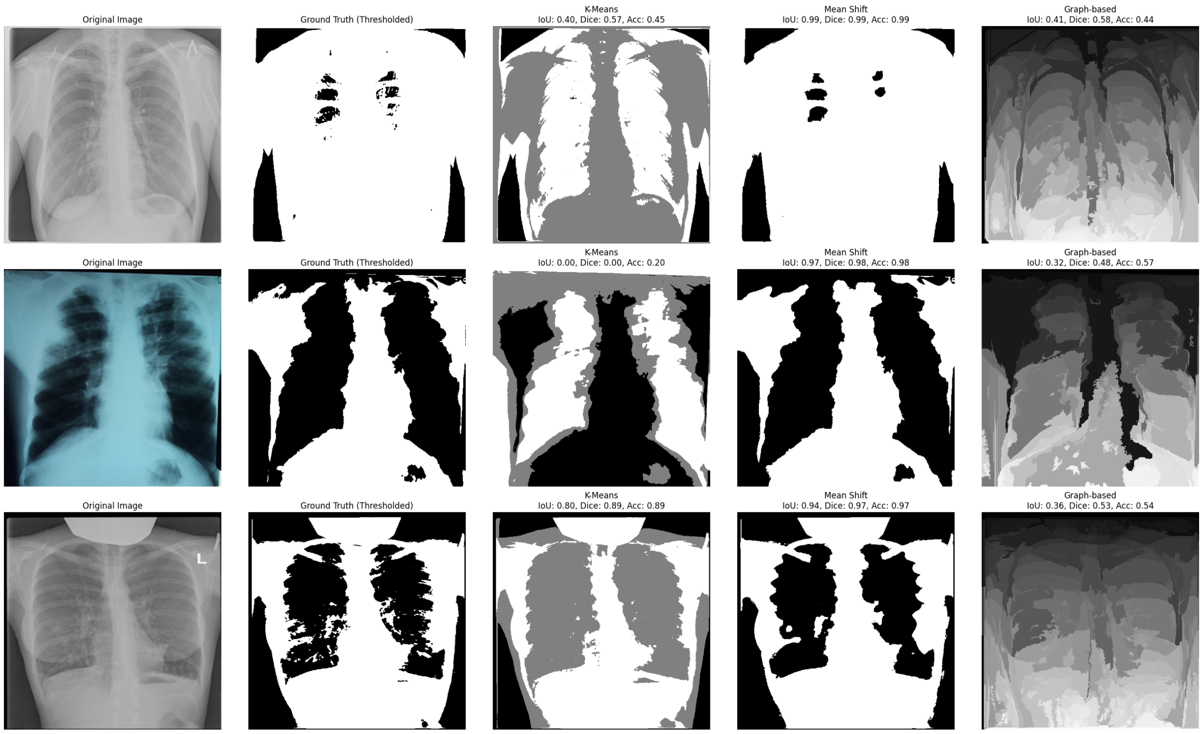


3. Comparative Analysis of Segmentation Techniques for Chest X-ray Images:

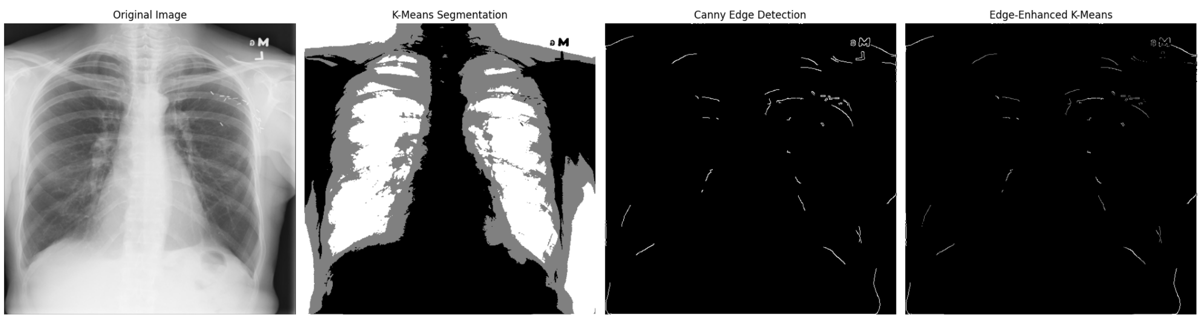
4. Region Growing Segmentation with Connected Component Analysis (CCA) for Noise Removal in Chest X-ray Images:



5. **Lung X-ray Segmentation: Comparison of K-Means, Mean Shift, and Graph-Based Methods:**



6. **Lung X-ray Image Analysis: K-Means Segmentation and Edge Detection:**



CONCLUSION

This project successfully demonstrates a novel segmentation technique by integrating K-Means Clustering and Canny Edge Detection. The experimental results show:

→ Significant improvements in segmentation accuracy.
→ Reduction in noise interference.
→ Enhanced object extraction and boundary preservation.
→ Applicability across various image processing domains, including medical imaging and industrial defect detection.

FUTURE WORK

To build upon the current approach, several future enhancements can be explored:

1. **Deep-Learning-Based Segmentation:** Implement state-of-the-art models such as U-Net and Mask R-CNN to automate feature extraction and improve segmentation robustness.
2. **Real-Time Processing:** Optimize the proposed technique for real-time applications in medical diagnostics, surveillance, and automated quality inspection.
3. **Automated Parameter Tuning:** Introduce adaptive mechanisms to automatically fine-tune segmentation parameters based on image characteristics, reducing manual intervention and enhancing performance across different datasets.

By integrating these advancements, the project can evolve into a more comprehensive and efficient segmentation framework with broader real-world applications.

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