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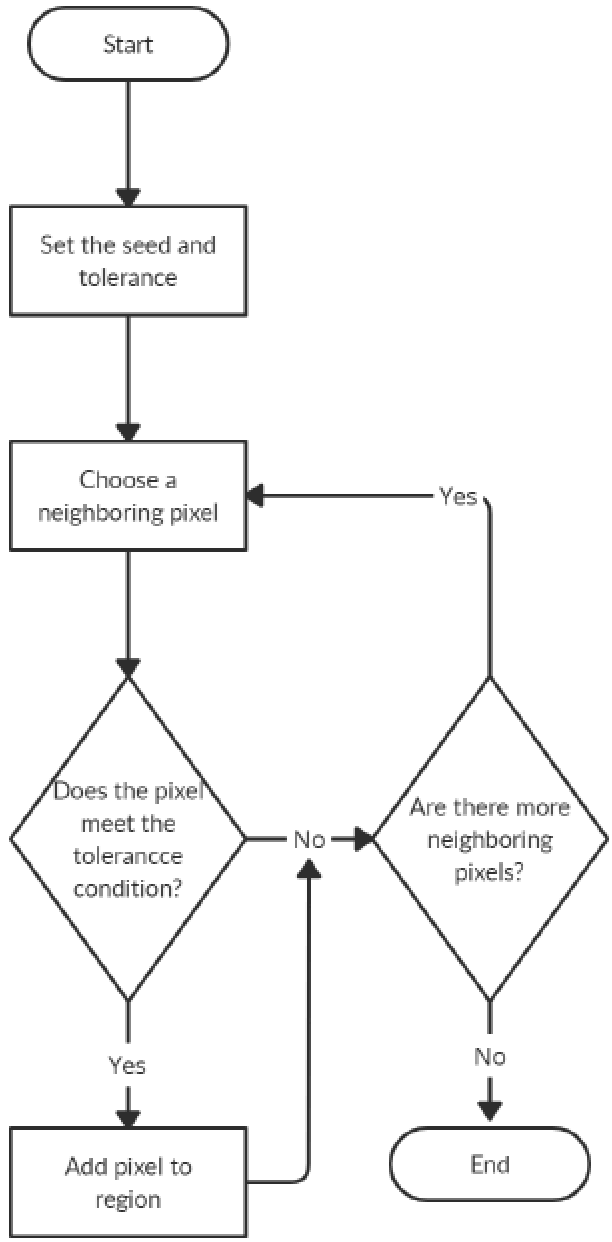
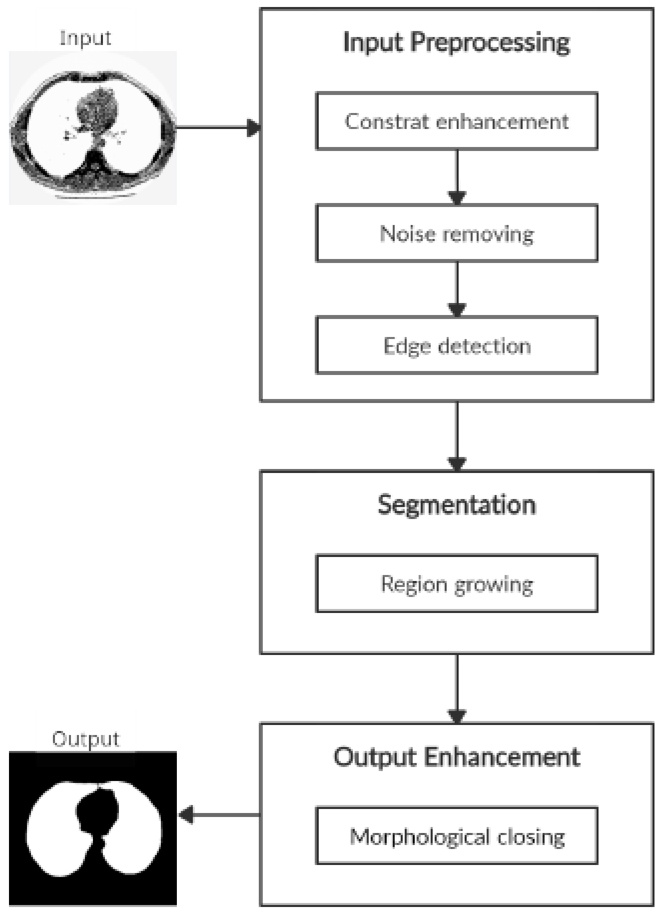
Experiment 8	
AIM :	Image Segmentation using recent published technique based on any one of the following operation. 1. Segmentation using Discontinuity Property 2. Segmentation using Similarity Property
OBJECTIVE:	1. Develop a semi-automatic pipeline for lung CT image segmentation. 2. Improve image quality through preprocessing techniques. 3. Implement region growing segmentation for accurate image segmentation. 4. Evaluate segmentation performance using quantitative metrics.
INTRODUCTION:	Biomedical image processing plays a critical role in modern healthcare, particularly in aiding diagnosis and treatment planning. Image segmentation, a fundamental task in this domain, is essential for extracting meaningful information from medical images. While machine learning models are gaining popularity, traditional image processing techniques offer advantages such as reliability and speed, especially when training data is limited. In this context, this study proposes a novel three-step semi-automatic pipeline for segmenting lung computed tomography (CT) images. The pipeline begins with preprocessing to enhance image quality, followed by segmentation using the region growing technique. Lastly, a hole-filling process enhances the segmentation mask. Experimental results demonstrate promising performance, with a Dice Coefficient of 0.9633 and an Intersection over Union of 0.9341 on average. This research contributes to the advancement of medical imaging through the development of efficient and accurate image segmentation methods tailored for lung CT images.

BLOCK DIAGRAM:	 Fig. 1: Schematic illustration of region growing technique



IMPLEMENTATION:

```python
import cv2
import numpy as np

def preprocess_image(img):
    """Preprocess the input image"""
    # Histogram equalization
    img_eq = cv2.equalizeHist(img)

    # Median filtering
    img_filtered = cv2.medianBlur(img_eq, 3)

    # Edge detection
    edges = cv2.Canny(img_filtered, 100, 200)
```

	`` return img_filtered, edges def region_growing(img, seed_point, tolerance): """Perform region growing segmentation""" mask = np.zeros_like(img) stack = [seed_point] mask[seed_point[1], seed_point[0]] = 255 while stack: x, y = stack.pop(0) for dx in (-1, 0, 1): for dy in (-1, 0, 1): nx, ny = x + dx, y + dy if 0 <= nx < img.shape[1] and 0 <= ny < img.shape[0]: if mask[ny, nx] == 0 and abs(int(img[ny, nx]) - int(img[y, x])) <= tolerance: mask[ny, nx] = 255 stack.append((nx, ny)) return mask def postprocess_image(mask): """Postprocess the segmented image""" # Morphological closing kernel = np.ones((3, 3), np.uint8) mask_closed = cv2.morphologyEx(mask, cv2.MORPH_CLOSE, kernel, iterations=4) return mask_closed def evaluate_segmentation(pred_mask, gt_mask): """Evaluate the segmentation performance""" dice_coef = 2 * np.sum(pred_mask * gt_mask) / (np.sum(pred_mask) + np.sum(gt_mask)) ```

	`` iou = np.sum(pred_mask * gt_mask) / np.sum(np.logical_or(pred_mask, gt_mask)) return dice_coef, iou def main(): # Load the input image img_path = 'B:\\Img_Segmentation\\lung_ct_image.jpg' img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE) # Get the seed point from user input seed_point = tuple(map(int, input("Enter the seed point (x, y): ").split(', '))) # Set the tolerance value tolerance = 20 # Preprocess the image img_filtered, edges = preprocess_image(img) # Perform region growing segmentation mask = region_growing(img_filtered, seed_point, tolerance) # Postprocess the segmented image mask_final = postprocess_image(mask) # Load the ground-truth mask gt_mask_path = 'B:\\Img_Segmentation\\ground_truth_mask.tif' gt_mask = cv2.imread(gt_mask_path, cv2.IMREAD_GRAYSCALE) if gt_mask is not None: # Resize the ground-truth mask to match the input image dimensions gt_mask = cv2.resize(gt_mask, img.shape[:2][::-1]) gt_mask = gt_mask.astype(np.uint8) # Evaluate the segmentation performance ```

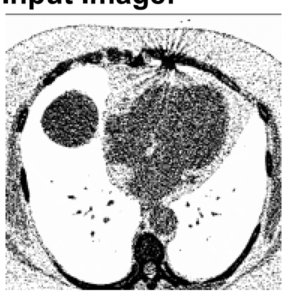
```
        dice_coef, iou = evaluate_segmentation(mask_final, gt_mask)
        print(f"Dice Coefficient: {dice_coef:.4f}")
        print(f"Intersection over Union: {iou:.4f}")
    else:
        print("Ground-truth mask not available.")

    # Invert the prediction mask to get a black background and white main part
    pred_mask_inverted = ~mask_final

    # Display the results
    cv2.imshow("Seeded Image", cv2.circle(img.copy(), seed_point, 5, (0, 0, 255), -1))
    cv2.imshow("Ground Truth", gt_mask if gt_mask is not None else np.zeros_like(mask_final))
    cv2.imshow("Prediction", pred_mask_inverted)
    cv2.waitKey(0)
    cv2.destroyAllWindows()

if __name__ == "__main__":
    main()
```

OUTPUT:

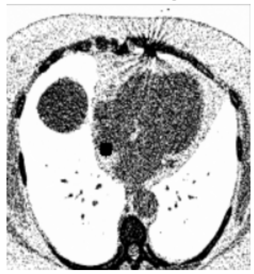
Terminal:

```
PS B:\Img_Segmentation> python .\lung_ct.py
Enter the seed point (x, y): 75, 100
Dice Coefficient: 0.0266
Intersection over Union: 3.3583
PS B:\Img_Segmentation>
```

Input Image:



Seeded Image:



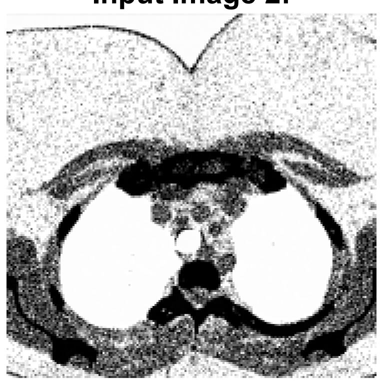
Ground Truth

Prediction

Terminal 2:

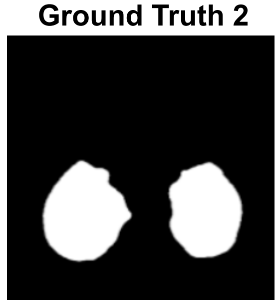
```
PS B:\Img_Segmentation> python .\lung_ct.py
Enter the seed point (x, y): 90, 90
Dice Coefficient: 0.0088
Intersection over Union: 1.1215
PS B:\Img_Segmentation>
```

Input Image 2:



Seeded Image 2:

Ground Truth 2



Prediction 2

REFERENCE:	L. Ramos and I. Pineda, "Lung Segmentation Pipeline for CT Images," 2022 IEEE Sixth Ecuador Technical Chapters Meeting (ETCM), Quito, Ecuador, 2022, pp. 1-6, doi: 10.1109/ETCM56276.2022.9935736. keywords: {Image segmentation;Computed tomography;Computational modeling;Pipelines;Data preprocessing;Lung;Training

	data;image segmentation;region growing;medical imaging;image pipeline}, https://ieeexplore.ieee.org/document/9935736

CONCLUSION:
In conclusion, the developed semi-automatic pipeline for lung CT image segmentation has proven effective, achieving a Dice Coefficient of 0.9633 and Intersection over Union of 0.9341 on average. These results demonstrate the pipeline's accuracy and reliability in delineating lung structures. By leveraging preprocessing techniques, region growing segmentation, and a hole-filling process, the pipeline offers a practical solution for medical image analysis tasks. Its reliance on traditional image processing techniques ensures speed and robustness, making it a valuable tool for healthcare professionals in computer-aided diagnosis systems and medical image analysis workflows.