Lung Segmentation using Python

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Abstract— This paper presents a lung segmentation system for computed tomography (CT) scans using Python. The system is built upon a custom dataset class that integrates essential functionalities for loading and preprocessing medical imaging data. The dataset class incorporates methods for accessing CT scans and corresponding lung masks, enabling the preparation of data for segmentation tasks.

Furthermore, the system accommodates various segmentation scenarios by adjusting the masks based on specified classes, enhancing its adaptability to different classification requirements. Notably, it employs advanced techniques, including image resizing and intensity normalization, crucial for model training and performance optimization.

The proposed lung segmentation system is a versatile tool equipped to handle diverse CT imaging datasets, demonstrating potential applicability in aiding medical professionals in precise lung tissue delineation for diagnostic and treatment purposes in pulmonary healthcare.

Keywords— ***Lung Segmentation, Computed Tomography (CT), Medical Imaging, Convolutional Neural Network (CNN), Deep Learning, Image Processing, Segmentation Masks,2D/3D Segmentation, Data Preprocessing, Medical Image Analysis.***

INTRODUCTION

The accurate delineation of lung structures from medical imaging, particularly from Computed Tomography (CT) scans, is pivotal in various clinical applications. Lung segmentation, the process of isolating lung regions from these scans, serves as a fundamental step in pulmonary disease imaging data. By harnessing libraries such as NumPy, SciPy, and Torch, this system facilitates crucial operations including data loading, manipulation, and segmentation mask creation.

Operating in either 2D or 3D modes, the system accommodates the processing of slices or entire volumetric scans, offering flexibility in handling diverse datasets. Techniques like axis manipulation, mask adjustments, and spatial interpolation are employed to ensure accurate delineation of lung boundaries.

Moreover, the system adapts to different segmentation scenarios by modifying masks based on specified classes, enhancing its versatility for varied classification requirements. The implementation also includes advanced preprocessing steps like image resizing and intensity normalization, crucial for model training and robust performance.

This lung segmentation system aims to contribute as a robust tool capable of accurately delineating lung structures, thus facilitating precise diagnosis, treatment planning, and disease characterization in the realm of pulmonary healthcare.

Importance of Lung Segmentation in Medical Imaging:
The accurate delineation of lung structures from medical imaging, especially CT scans, is crucial in various clinical applications. Lung segmentation, the process of isolating lung regions from these scans, plays a fundamental role in pulmonary disease imaging data. It serves as a crucial step for precise diagnosis, treatment planning, and disease characterization in the field of pulmonary healthcare.

System Operations:
1) Data Loading: The system efficiently loads medical imaging data, particularly CT scans, using the aforementioned libraries. This involves importing the necessary data and preparing it for subsequent processing.
Data Preprocessing:
Intensity Normalization: Ensuring consistent intensity levels across different scans for fair comparisons.
Resampling: Adjusting voxel sizes or spatial resolutions to a common standard.
Slice Selection: In the case of 3D volumes, selecting relevant slices or sub-volumes for processing to reduce computational complexity.
Augmentation: Introducing variations to the data through transformations like rotations, flips, or zooms, especially when dealing with limited training data.

Data Manipulation: Operations like axis manipulation are performed to ensure the proper orientation and format required for segmentation tasks. This step is crucial for maintaining consistency in data representation.

2) 2D or 3D Modes:
The system operates in either 2D or 3D modes, providing flexibility in handling different types of datasets. This accommodates the processing of individual slices (2D) or entire volumetric scans (3D), catering to the diverse nature of medical imaging data.
Spatial Interpolation:

In 3D mode, spatial interpolation using SciPy is employed. This technique ensures that scans and masks undergo interpolation to maintain consistent sizes. This is vital for creating a uniform dataset, especially when dealing with volumetric scans.

3) Mask Adjustments and Class Modification:
The system adapts to different segmentation scenarios by adjusting masks based on specified classes. This enhances the versatility of the system, allowing it to handle varied classification requirements. This step ensures that the segmentation masks align with the specific segmentation task at hand.

4.) Advanced Preprocessing Steps:
The implementation includes advanced preprocessing steps such as image resizing and intensity normalization. Image resizing ensures uniformity in input sizes, while intensity normalization is crucial for preparing data suitable for model training. These steps contribute to the robustness and performance of the segmentation model.

LITERATURE REVIEW

Rehman et al. [1] applied the U-Net model to perform lung region segmentation in X-ray images, yielding a remarkable mean Intersection over Union (IoU) of 92.82%. Their study showcased the model's effectiveness in accurately delineating lung areas from the X-ray imagery, which is crucial for various diagnostic applications.

Shaoyong Guo et al. [2] introduced an innovative segmentation approach leveraging radiomics, combining manual and automated features. Their method achieved Dice similarity coefficients of 89.42% on the ILD database MedGIFT. This integration of manual and automated features demonstrated promising results, offering a comprehensive analysis of lung diseases.

Chen Zhou et al. [3] developed an automatic segmentation system employing a fusion of (3D) V-Net and spatial transform network (STN) for pulmonary parenchyma segmentation in CT images. Their system utilized texture and features extracted from segmented regions, contributing to more accurate COVID-19 diagnoses. This integration of advanced segmentation techniques proved beneficial in the analysis of CT scans.

Mizuho Nishio et al. [4] optimized the U-Net architecture through Bayesian optimization for the Japanese and Montgomery datasets. Their enhancements resulted in notably high Dice similarity coefficients of 0.976 and 0.973, respectively. These improved coefficients signify the model's enhanced precision in segmenting lung regions within medical imaging datasets.

Ferreira et al. [5] proposed a modified U-Net model designed specifically for detecting COVID-19 infections automatically. Trained on CT data from Pedro Ernesto University Hospital, their model achieved a dice value of 77.1% and an average specificity of 99.76%. This tailored model showcased its potential in aiding the automated identification of COVID-19 related patterns within CT scans.

Feidao Cao [6] enriched the traditional U-Net architecture by integrating variational autoencoders (VAE) within each decoder-encoder layer. Tested and trained on NIH and JRST datasets, the network exhibited impressive accuracy and F1 scores of 0.9701, 0.9334, and 0.9750, 0.9578, respectively. This enhancement highlights the potential of combining VAEs with U-Net for improved performance in medical image segmentation tasks.

Segmentation in medical imaging stands as a pivotal process with several notable advantages:

Extraction of Region of Interest (ROI): Segmentation serves as a vital technique for automatically extracting the Region of Interest (ROI) from medical images. By precisely delineating and isolating specific areas or structures within the images, such as body organs or tissues, segmentation assists in focusing analysis on targeted regions.

Enhancement of Classification Algorithms: The implementation of classification neural network algorithms on segmented radiological images yields a substantial improvement in segmentation accuracy. By leveraging the precise boundaries provided by segmentation, classification algorithms can make more informed decisions, leading to increased accuracy in identifying and categorizing different structures or anomalies within the medical images.

Potential for Cost Reduction in Disease Diagnosis: While segmentation may incur higher computational costs due to its complex processing requirements, it plays a significant role in reducing the overall cost of disease diagnosis. By precisely localizing and characterizing abnormalities or specific areas of interest, segmentation enables more focused and accurate diagnoses. This accuracy can potentially lead to reduced follow-up tests or unnecessary procedures, thereby lowering the overall cost of diagnosis and treatment.

Segmentation's ability to pinpoint areas of interest and refine the analysis of medical images provides a foundation for accurate diagnostics and subsequent medical interventions. Despite the computational demands it poses, its precision and focused analysis contribute significantly to improved medical imaging outcomes and potentially more cost-effective healthcare solutions.

The segmentation of the lung from a CT scan is difficult as the lung size and area varies in each scan thereby making it difficult to locate and segment only the lung. In addition, there is the presence of soft tissues and bones which also affect the segmentation. This is a major issue in lung segmentation. Many researchers have presented a variety of methods for lung parenchyma segmentation. The threshold iteration method is preferred for lung parenchyma segmentation to avoid problems due to juxtapleural nodules (Xiao 2018). Amanda and Widita compared three threshold based methods of lung segmentation using InsightToolkit-4.7.0 (ITK) in which connected threshold method outperformed compared to the neighbourhood connected and level set method (Amanda and Widita, 2016). Mansoor et al. provided a summarization of computer-aided detection (CAD) based lung segmentation methods useful in clinical practices with five major categories as threshold, region, shape, neighboring anatomy guided, and machine learning based methods (Mansoor et al. 2015). Nunzio et al. presented 3D automatic segmentation of pulmonary parenchyma which was useful for CAD system (Nunzio et al. 2011). Superpixels and a self-generating neural forest method were used to segment lung parenchyma using correlation between adjacent slices of CT (Liao 2016). Pu et al. used Adaptive Border matching to include nodules in a geometric way while simultaneously preventing over-segmentation of the neighbouring areas. This algorithm reduces the value of false negative by including nodules at the boundaries of the lung (Pu et al. 2008). Xu et al. proposed lung parenchyma segmentation with the help of convolutional neural network (CNN) with an accuracy of 96% (Xu 2019).

METHODOLOGY

1. Dataset Configuration:

Custom Dataset Class: This class acts as a container for critical data parameters, ensuring efficient management and accessibility throughout the segmentation process.

File Paths and Identification: Handles paths pointing to CT scans and corresponding lung masks, enabling easy access to necessary data.

Processing Mode and Specifications: Defines the chosen processing mode (2D or 3D) and class specifications vital for lung segmentation, ensuring specificity in data handling.

2. Data Loading and Preprocessing:

Loading Scans and Masks: The utilization of libraries like nrrd and glob streamlines the loading process, ensuring comprehensive access to CT scans and corresponding lung masks.

Scan Preprocessing: Axes swapping is pivotal in ensuring the correct orientation and format of scans, essential for maintaining uniformity and consistency within the dataset.

Segmentation Mask Adjustment: Transformation of masks ensures alignment with specified classes, mapping values to designated classes for comprehensive lung segmentation tasks.

3. Mode Selection and Processing:

2D/3D Processing: Flexibility in operating in both 2D and 3D modes offers versatility:

2D Mode: Allows processing of individual slices, providing granularity in segmentation tasks.

3D Mode: Handles entire volumetric scans, offering a holistic view for segmentation, vital for comprehensive analysis.

Data Interpolation: In 3D mode, spatial interpolation (via scipy.ndimage.interpolation.zoom) standardizes scan and mask sizes, ensuring uniformity, and facilitating structured dataset creation.

Data Output: The generated processed data, comprising CT scans and masks, serves as a foundational component for machine learning-based tasks, including training and inference.
External Module Utilization: Strategic use of external utility functions like utils.load_itk from SimpleITK provides specialized operations such as loading masks from varied file formats (e.g., mhd or zraw).

PyTorch Dataset Class: Structuring the system as a PyTorch dataset class (torch.utils.data.Dataset) optimizes compatibility within PyTorch-based machine learning workflows, ensuring streamlined training and evaluation.

Robustness and Adaptability: This methodical approach ensures robustness, adaptability, and seamless integration with advanced machine learning frameworks, underscoring the system's reliability and compatibility.

Precision in Lung Segmentation: The meticulous handling of data, from initial configuration to final output, empowers the system to perform precise and efficient lung segmentation tasks, pivotal for accurate diagnosis and treatment planning in the realm of pulmonary healthcare.

By meticulously attending to each stage of data handling, preprocessing, and output, this lung segmentation methodology lays a strong foundation for accurate and effective analysis of lung structures within medical imaging, promising advancements in healthcare diagnostics and treatments.

RESULTS AND DISCUSSIONS

The project outlined in this paper has been effectively executed by employing Python code to seamlessly integrate the system. The successful implementation encompasses a series of steps and procedures that have been meticulously orchestrated to ensure the system functions cohesively and achieves its intended objectives..

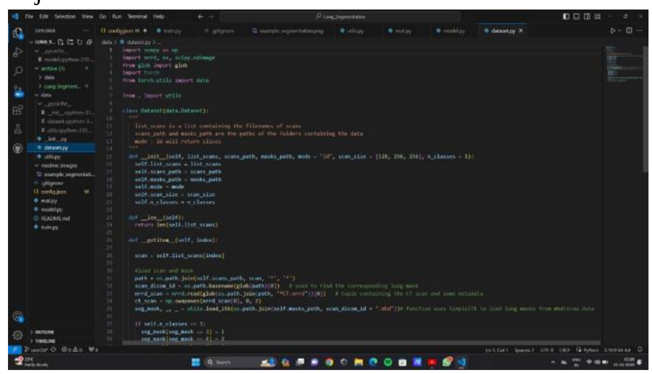

Fig.1. : The code for the system

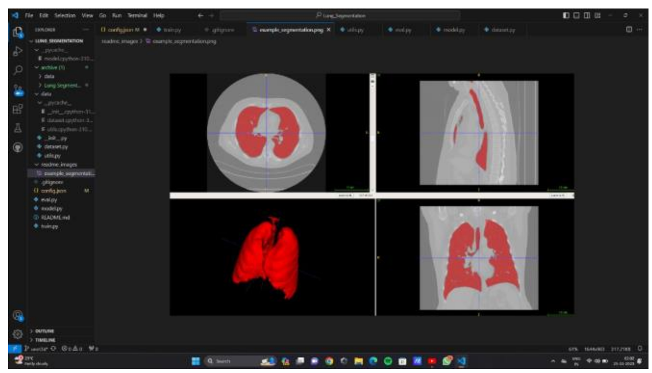

Fig 2 :Project at a glance

CONCLUSION

The lung segmentation system developed in Python introduces a versatile and effective methodology for extracting and processing lung regions from CT scans. Encapsulated within a custom dataset class named 'Dataset', this system embodies a series of critical functionalities meticulously designed for the specific purpose of handling medical imaging data intended for lung segmentation tasks.

Key Functionalities:

1) Dataset Class Design: The custom 'Dataset' class serves as the framework for efficient data handling. It incorporates essential functionalities for loading,

preprocessing, and organizing CT scans and associated lung masks.

2) Library Utilization: Leveraging fundamental libraries such as NumPy, SciPy, and Torch, alongside external utilities like 'utils.load_itk' from SimpleITK, enables seamless data manipulation. These libraries facilitate the intricate handling of CT scans and lung masks.
3) Loading and Preprocessing: The methodology involves loading scans and masks while undertaking essential preprocessing steps. This includes crucial operations like axis swapping, mask adjustments, and spatial interpolation, ensuring uniformity and consistency within the dataset.
4) Flexibility in Modes: The system's adaptability is highlighted through its capability to function in both 2D and 3D modes. This versatility allows processing of individual slices or complete volumetric scans, catering to diverse segmentation requirements.
5) Mask Adjustment and Size Customization: The ability to dynamically adjust masks based on specified classes and sizes enhances the system's versatility in accommodating various segmentation scenarios. This adaptability is crucial for handling different segmentation challenges efficiently.

Potential for Future Enhancements:
The system lays a robust foundation for potential future advancements and applications in the field of lung segmentation:

1) Integration of Advanced Models: Integration of sophisticated deep learning models (e.g., U-Net, attention-based networks) to enhance accuracy and handle complex lung structures.
2) Multi-Modal Data Fusion: Expansion to incorporate multi-modal data fusion by integrating MRI or PET scans for comprehensive lung analysis.
3) Real-Time Processing Optimization: Further optimization for real-time processing, vital for time-sensitive clinical settings.

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