PulmoVision: An End-to-End 3D Slicer Module Pipeline for CT Lung Tumor Radiomics with 3D U-Net Segmentation

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Introduction and Related Work

Radiomics is the extraction of quantitative features from medical imaging that provides biological information that can yield insights about disease processes (McCague et al., 2023). This field of study is one of many different "-omics" fields that has been founded due to rapid technological advancement and the associated shift in medical imaging from qualitative interpretation to quantitative analysis (Avery et al., 2022). In radiomics specifically, due to its wide range or applicability across circumstance and the body, several imaging modalities including computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), single-photon emission computed tomography (SPECT), and ultrasound (US) can be used to derive features.

These features are descriptors of clinically relevant information contained in the images such as tissue shape, intensity and structure. Deep analysis of such features is capable of creating new opportunities to improve disease detection, increase prognostic accuracy, and timely treatment decisions. Furthermore, radiomics-based models have already been attempted to predict variables such as tumor aggressiveness, patient survival, treatment response and even genetic profiles, showing their potential impact for oncology, and a range of other conditions. Its present relevance is deepened by how it aligns with both artificial intelligence and telemedicine (Avery et al., 2022).

Since the amount of research and clinical work being done with radiomics has substantially increased recently with a 178% growth rate from 2013 to 2018, a standardized step-by-step workflow has been created, in the hopes of greater unified understanding of the field's methodology and easier reproducibility for future research (Avery et al., 2022). This workflow includes a step for image acquisition, image segmentation, feature extraction, analysis, and clinical application. However, as is common with rapidly advancing fields, innovation in imaging has often outpaced integration. In other words, while we do have powerful methods for preprocessing, segmentation, visualization, and analysis embedded in the general standardized workflow, these processes emerged independently and are themselves not standardized, resulting in fragmented processes that are difficult to reproduce and inefficient to use (Floca et al., 2024; Van Timmeren et al., 2020). The workflow contains individual processes that have many software platforms. In addition, different research groups use different tools such as 3D Slicer, FreeSurfer, ITK-SNAP, ImageJ, or deep learning models such as U-Net (Avery et al., 2022). Thus, these processes are un-standardized, disjointed and lack integration or a pipeline. Relying on multiple software solutions for all the processes requires compatibility adjustments, and leads to slow analysis and an increase in the risk for errors, ultimately hindering the accuracy and the reliability of the output (Jamzad et al., 2025).

This problem is not only prevalent in Radiomics but across many biomedical imaging disciplines. Mass spectrometry imaging (MSI) is similarly hindered by the lack of integrated, scalable end-to-end, seamless tools. However, in this case there is a newly structured pipeline to fix this exact problem. MassVision is a 3D slicer module developed to integrate all aspects of MSI data handling into a single tool (Jamzad et al., 2025). As the authors state, "bridging these gaps requires a new generation of software capable of supporting end-to-end workflows, enabling seamless data integration and AI deployment (Jamzad et al., 2025, p. 2). More specifically MassVision's development of this application allowed for visualizing potentially cancerous regions in histology images in a single pipeline which supported dataset curation, multislide alignment, preprocessing, statistical analysis, AI model training, and deployment of AI models. While MassVision's application lies in MSI and histology, its contribution lies in demonstrating how integration across several fragmented stages can make a research method more reproducible and clinically useful.

Within the field of radiomics one of the most clinically significant applications lies in lung tumor segmentation from CT imaging. This is due to lung cancer being the leading cause of cancer related mortalities worldwide as of 2020, and CT imaging being the foundational imaging technique for both initial detection and staging (Islam & Walker, 2013; World Health Organization, 2025). Furthermore, low-dose CT (LDCT) has been shown to reduce lung cancer mortality (Kadia et al., 2021). However, in practice it is common for manual segmentation, or semi-manual segmentation (using algorithms for region growing or segmentation) by physicians or researchers to occur though this is time consuming and can introduce observer bias, which then requires intra- and inter-observer investigation and reporting (Avery et al., 2022; Van Timmeren et al., 2020). This lack of standardization can slow the analysis, and impugn on the reproducibility of the methods, as even small differences in segmentation can result in the extraction of unstable radiomic features (McCague et al., 2023). Instead a newer method is emerging that uses deep learning-based image segmentation which avoids this intra- and inter-observer variability and increases objectivity (Timeren et al., 2020). Typically the type of deep learning architecture that is used is a U-Net, or a convolutional neural network (CNN) that adheres to a symmetric encoder and decoder with structure that forms a U-shape and allows for the propagation of spatial information to higher resolution layers (Ronneberger, 2015). For volumetric imaging, like CT, this design was expanded upon through the development of the 3D U-Net which replaces all 2D operations with their 3D counterparts, allowing for the model to capture spatial context across three axes and perform segmentation directly on 3D volumes (Çiçek et al., 2016). This architecture has already shown success in CT lung tumor application, such as the extraction and segmentation of suspicious lung nodules (Zhao et al., 2018). More recently an altered version of 3D U-net (Recurrent Residual 3D U-Net) has shown state of the art performance for lung segmentation on public databases LUNA16 and VESSEL12 (Kadia et al., 2021). These results justify the usage of 3D U-Net for segmentation within a standardized pipeline for the analysis of lung CT scans.

Motivation

Although MassVision has addressed this problem of fragmented processes within the field of MSI, a parallel tool has yet to be created for Radiomics. In the context of lung cancer, where CT imaging has been shown to be the foundational methodology for detection and diagnosis, tumor segmentation remains highly variable, thus limiting reproducibility and slowing the production of results. While 3D U-Net has been shown to be successful in both lung tumor segmentation and whole lung segmentation, it is implemented as an individual method for segmentation, it is not integrated into a standardized workflow. This project aims to address this gap in the literature by developing an end-to-end 3D slicer module specifically for lung tumor detection and diagnosis. Through embedding all the individual processes of image acquisition, image segmentation, feature extraction, analysis, and clinical application into one single pipeline, this module could eliminate fragmentation, improve reproducibility, and lower the technological boundary required for widespread adoption in both clinical and research formats.

Objectives

The main objective for this project is to design and implement a 3D slicer module that consolidates the workflow for CT lung tumor radiomics into one pipeline. In order to accomplish this, the system must integrate all of the major steps of the workflow including preprocessing, automated segmentation, feature extraction, and visualization, into the proposed one-click interface. To do this effectively the pipeline will include an AI-segmentation method using a 3D U-Net model within the workflow. The goal is not to develop a new state of the art model, but instead to embed a functional reproducible AI segmentation component into a full end-to-end system inspired by the design philosophy of MassVision.

Novelty

Although there are many tools and solutions available for analysis of radiological data, a lot of tools don't provide simple processes for 3D analysis. Some scientists rely on manually labeling regions of interest or execute separate applications for preprocessing and segmentation. MassVision is a great demonstration of reliable end-to-end pipeline for mass spectrometry imaging. The model that is worked on for this project is inspired by the philosophy of workflow of MassVision. This is extended to the domain of radiology and will be executed in a 3D Slicer program. In this way, the novelty of this project is achieved by having this model work as a template for an end-to-end pipeline with a simple interface. If there is a better AI component, the new AI component can easily replace the previous AI component so that the performance of the model is upgraded.

Proposed Method

This model takes 3D volumetric input and segments within 3D Slicer. This will be done in a single execution. For training this model, simulated tumor volumes will be used as a dataset; it will produce images that indicate proper segmentation. Before segmentation, all the dataset will undergo preprocessing phases that includes, rescaling, resizing, and intensity normalization for the input lung data. Segmentation in this model will be performed by a lightweight 3D U-Net. Then output will be the preprocessed CT image with the segmentation on target tumor. Rather than achieving high performance in terms of accuracy, scalability, and latency, this model will be focused on executing end-to-end pipelines executed by single click.

The proposed model is for providing 3D segmentation for regions of interest, and it is compatible with 3D Slicer to display images from axial, coronal, and sagittal views. The output of this model is the preprocessed images with segmentations and quantitative features, then the modelled 3D structures will be saved for further use.

Achieving clinical accuracy is not a key concept of this model. The main objective is to utilize the 3D U-net model for radiomics workflows. Further upgrading can be done by pre-training or implementation of networks with higher performance. The current limitation of this module is that it is trained on simulated data, and the size of the testing set will not be sufficient. However, this method of approach will suggest new perspectives towards medical imaging by providing 3D compatibility and a simple end-to-end pipeline.

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