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3D Reconstruction Of Organs From CT And MRI Scan For Enhanced Diagnostic Visualization.

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Abstract— Medical imaging is now a central part of contemporary healthcare, allowing non-surgical viewing of inner anatomy using technologies such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). Traditional 2D results of these technologies, though, leave clinicians to visually inspect cross-sectional images individually, an enterprise vulnerable to inefficiency and subjective judgment. In an attempt to solve this, 3D reconstruction has become a revolutionary method, transforming 2D scan data into interactive 3D volumetric models that provide comprehensive insights into intricate anatomical structures. This paper introduces a system aimed at reconstructing and visualizing 3D organ models from CT/MRI data. The pipeline includes preprocessing phases such as HSV color space conversion and morphological operations (erosion, dilation, closing) to enhance image quality and segment target areas. Marching Cubes algorithm is then utilized to reconstruct high-accuracy 3D meshes from the preprocessed slices. With the integration of 2D scans to dynamic 3D representations, the framework facilitates diagnostic accuracy, enables personalized surgical planning, enhances treatment assessment, and acts as an education tool for visualizing pathological and physiological structures in depth.

Keywords— 3D reconstruction, medical imaging, CT scan, MRI, image segmentation, Marching Cubes algorithm, diagnostic visualization, image preprocessing

I. Introduction

Organs are basic biological structures, and their medical assessment now more and more depends upon high-resolution imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). Although these machines create precise anatomical information, traditional diagnostic processes entail reading ordered 2D cross-sectional images a procedure that requires enormous time, is vulnerable to perceptual errors, and has difficulty communicating the complex 3D tissue relationships. To overcome these challenges, reconstructing 2D medical scans into volumetric models has emerged as a critical advancement, enabling clinicians to interact with spatially accurate representations of anatomical structures. Among reconstruction algorithms, Lorensen and Cline's pioneering Marching Cubes algorithm is a staple for mapping volumetric data to high-fidelity 3D surface meshes. Interpolating isosurfaces between voxel grids, it builds triangulated models that maintain morphological features of organs. The reconstruction process starts with preprocessing procedures, such as image improvement (contrast adjustment, filtering out noise) and segmentation, in order to separate organ boundaries within CT/MRI datasets. These cleaned slices are then combined and processed by algorithms such as Marching Cubes to create volumetric renderings. Such models improve diagnostic accuracy by uncovering spatial anomalies undetectable in 2D workflows, and also facilitate surgical simulation, therapy evaluation, and patient communication. This study outlines a systematic framework for transforming CT/MRI scans into 3D organ reconstructions, emphasizing clinical applicability. Section II reviews foundational concepts, while Section III details the methodology, encompassing preprocessing, segmentation, and reconstruction stages.

II. RELATED WORKS.

A. Elements of Medical Image Processing (Emami, Janney, and Chakravarty, 2023) For segmentation, the authors highlight algorithms like thresholding, region-growing, and machine learning-driven approaches to delineate tumors or organs, ensuring precise 3D reconstruction. This feeds into visualization techniques, such as volume rendering and surface meshing, which transform segmented data into interactive models for clinical use—e.g., pre-surgical planning, radiotherapy targeting, or patient education. The framework also addresses computational challenges, such as optimizing GPU-accelerated pipelines for real-time processing of high-resolution datasets. Furthermore, the authors emphasize rigorous validation protocols, comparing algorithmic outputs against expert radiologist annotations to ensure clinical reliability and reproducibility. The interconnected stages ultimately improve diagnostic reliability and enablepersonalized, data-driven healthcare solutions.

B. Medical Image File Formats (Larobina and Murino, 2022) In their study, Wei-Hua, Larobina, and Murino examine critical medical imaging file formats—such as DICOM, NIfTI, and Analyze—and their role in ensuring interoperability and data integrity across medical image management systems. The authors emphasize how these standardized formats support seamless compatibility during image acquisition, reconstruction, and 3D visualization workflows. By addressing metadata preservation and structural consistency, their work underscores the necessity of robust file formats for maintaining diagnostic fidelity in clinical pipelines, enabling accurate integration of imaging data into AIdriven diagnostic frameworks and patient-specific therapeutic models.

C. How Does DICOM Work? (Pianykh, 2019) In Pianykh's work in elucidates the core functionalities of the DICOM standard, dissecting its data organization schemes, networked data exchange protocols, and integration with clinical workflows. By mastering these technical foundations, developers can enable seamless interoperability between medical imaging systems and advanced 3D visualization tools, ensuring reconstructed models retain diagnostic precision and clinical relevance.

III. METHODOLOGY.

This section outlines the architecture and implementation of a 3D visualization framework tailored for brain tumor segmentation via MRI. The pipeline begins with localizing tumor boundaries across sequential 2D MRI slices, followed by volumetric reconstruction algorithms to generate interactive 3D models (see Fig. 1). Comparative slice visualization— contrasting raw scans with segmented outputs—validates the system's pixel-wise annotation accuracy in isolating neoplastic tissues. By preserving spatial relationships and pathological features, the reconstructed models enhance multidisciplinary tumor board workflows, offering clinicians spatially contextualized data for stereotactic planning and dose optimization in radiotherapy.

A. Data Acquisition

A 3D reconstruction file represents a volumetric rendering of cerebral anatomy derived from CT or MRI scan data, optimized for high-precision diagnostic evaluation. The imaging protocol comprises axial slice sequences (typically 64 slices per patient) stored as 512 × 512-pixel PNG images, maintaining spatial resolution and grayscale fidelity. These cross-sectional datasets undergo volumetric stacking and interpolation to generate navigable 3D brain models, enabling clinicians to analyze intracranial structures—such as ventricles, lesions, or tumor margins—with submillimeter spatial context. The standardized PNG format ensures lossless compression for pixel-accurate reconstructions, critical for surgical simulation, radiation therapy planning, and longitudinal monitoring of neuropathological changes.

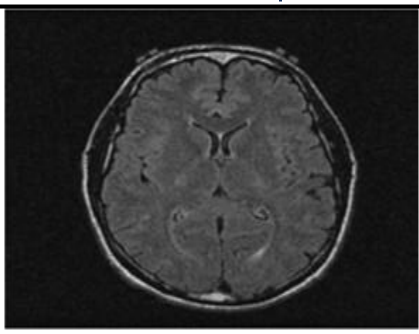
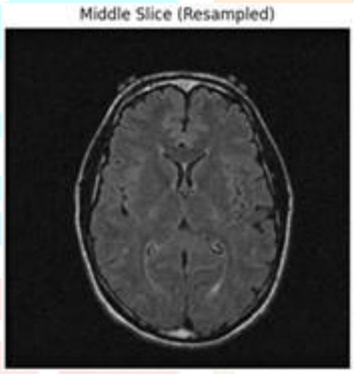


Fig 1. The Image of Brain

B. Image Preprocessing

Image This computational harmonization of raw DICOM/PNG datasets reduces cross-site variability and partial volume effects, establishing a robust foundation for volumetric modeling and AI-driven diagnostic frameworks. By preserving anatomical topology and enhancing quantitative imaging biomarkers, the pipeline bridges raw pixel data and clinically actionable insights— critical for automated lesion quantification, multiplanar reformatting, and tissue boundary delineation in neuro-oncology workflows. Computational rigor in preprocessing directly correlates with diagnostic fidelity in reconstructed 3D meshes, enabling millimeter-accurate surgical navigation and radiotherapy targeting.



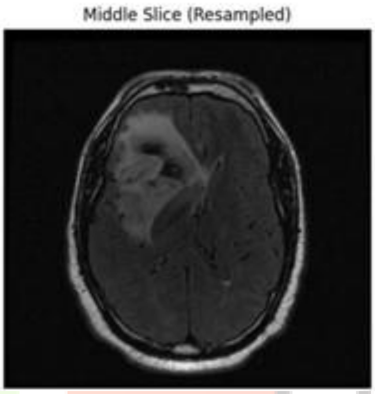


Fig 2. Axial MRI Brain Slice(Middle Slice, Resampled) Fig 3. Axial MRI Brain Slice (Top-Level Resampled View)

C.Segmentation

Segmentation refers to the task of detecting and separating individual organs or tissues from CT or MRI images. It is the process of labeling every pixel or voxel in the medical image as belonging to a specific anatomical structure, e.g., the liver, brain, or tumor. This is an important step for 3D reconstruction because it will only visualize the areas of interest in the resulting model. Segmentation techniques such as thresholding, edge detection, region growing, or deep learning-based approaches such as convolutional neural networks (e.g., U-Net) are used.

D. 3D Reconstruction

After segmentation, the 2D slices if images are combined to form a three-dimensional volumetric data set, which reflects the anatomical organization of the organ or tissue in multiple cross-sectional planes. For the formation of a high-resolution 3D surface model, the Marching Cubes algorithm is used, generating interpolated isosurfaces inside the volume and resulting in a triangular mesh boundary that outlines the segmented region. This technique transforms the segmented 2D data into a dynamic three-dimensional model, improving clinical applications like diagnosis, surgical planning, and medical training. The 3D reconstruction can be interactively rotated, zoomed, and examined to enhance understanding of anatomical spatial relations, especially with complicated structures such as tumors or organs.

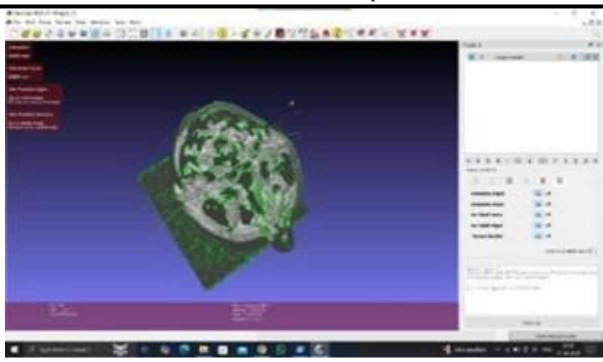


Fig 4. 3D Reconstruction of Brain

E. Visualization interface

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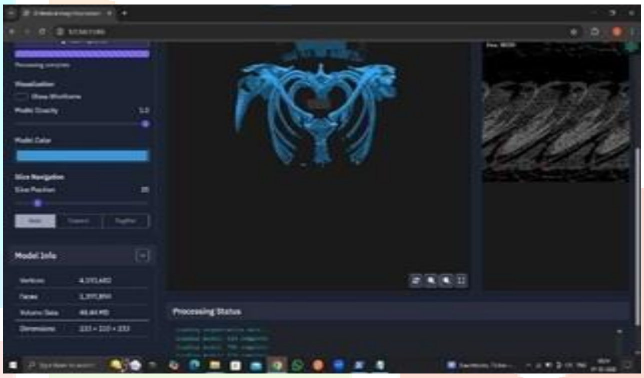

Fig 5. Web Interface

IV. IMPLEMENTATION

The process of producing 3D organ reconstructions from CT and MRI images is constructed with a suite of powerful tools and deep learning techniques. The Python backend utilizes PyDICOM to handle DICOM file processing and SimpleITK for image preprocessing, registration, and enhancement tasks. To render segmented 2D data into 3D models, the Visualization Toolkit (VTK) uses the Marching Cubes algorithm to produce accurate surface meshes. A Flask-driven API controls reconstruction processes and sends 3D model information to the frontend. The web-based interactive interface, built using HTML, JavaScript, and Three.js, allows for real-time rotation, zooming, and navigating 3D organ renderings by a user through a browser. For automatic segmentation, a convolutional neural network U-Net is trained to detect and segment anatomical structures or pathology (e.g., tumors) in scans, enhancing reconstruction speed and accuracy. These segmented areas are further handled by the backend to produce the final 3D visualizations.

The system enhances segmentation precision by training the U-Net model on a wide range of annotated medical scans, using techniques like data augmentation and transfer learning to adapt to different imaging styles and patient anatomies Segmentation output is verified with precision metrics (e.g., Dice metric) and optimized iteratively prior to 3D conversion. Backend performance is optimized for big data through the application of parallel processing libraries such as Dask, minimizing memory overhead in mesh creation. The AI training pipeline makes testing a different architecture, e.g., nnU-Net, for specific cases easy. The Flask API seamlessly serves the 3D models in GLB or STL format to the frontend, where Three.js provides silkysmooth real-time manipulation (rotation, zoom) through level-of-detail rendering. Clinicians can correct segmentation faults through an easy-to-use annotation tool, and these corrections are passed on to the AI model for ongoing learning. The system complies with medical standards (DICOM, HL7) and interfaces with hospital

PACS networks to ensure data security and workflow compatibility.

V. RESULTS & EVALUATIONS

The system proposed uses a U-Net architecture for automated segmentation of medical scans (CT/MRI) and couples it with the Marching Cubes algorithm to create high-fidelity 3D organ models. By utilizing open-source libraries like PyDICOM and SimpleITK, the framework ensures compatibility with DICOM standards and clinical workflows, reducing dependency on proprietary software. The integration of Three.js enables browser-based, interactive 3D visualization, allowing clinicians to manipulate models in real time for enhanced anatomical understanding. A modular API design further supports interoperability with external systems, such as EHRs or surgical planning tools. Although these benefits exist, segmentation accuracy of the system is affected by scan resolution, noise, and artifacts, potentially constraining performance on low-quality image sets. The exclusive current emphasis on binary segmentation also limits its applicability to single-organ assessment, excluding cases involving differentiation among overlapping structures (e.g., tumors abutting organs). Computational efficiency is also a challenge, as large or highresolution data sets can impede surface reconstruction and real-time rendering. Clinically, the instrument proves useful in preoperative planning (e.g., seeing tumor margins) and medical education, where dynamic 3D models complement standard 2D imaging. Nonetheless, clinical uptake would necessitate strict validation against gold-standard reconstructions and adherence to medical device regulations (e.g., data privacy, FDA approvals).

VI. CONCLUSION

The research concludes that the more CT scan images are used, the better is the quality of visual models in 3D for lung cancer, especially if 64 images are used, as this yields smoother and higher-resolution reconstructions. The results also show that the Marching Cubes algorithm provides better outputs if more slices are used in the 3D reconstruction process, since this method more accurately describes the volumetric extent of the tumor. In addition, experiments with mixed tumor morphologies showed that interference from surrounding organs can impair image quality, emphasizing the requirement for improved segmentation and image cropping methodologies to suppress such artifacts. Between the models tried, the second tumor model displayed lower noise levels and more accurate representation of cancerous structures relative to the first, emphasizing the role of shape and preprocessing on the accuracy of visualization.

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