CSE1906 - Mini Project
Final Review

LungCraft

Navigating Lungs with 3D Diagnostics

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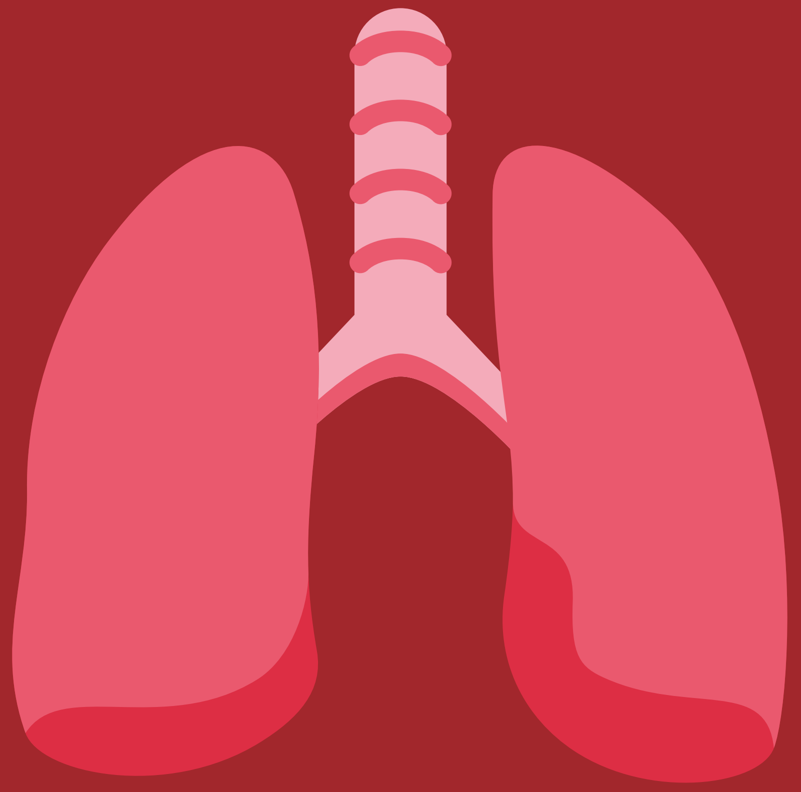
Guide: Dr. Suganya G



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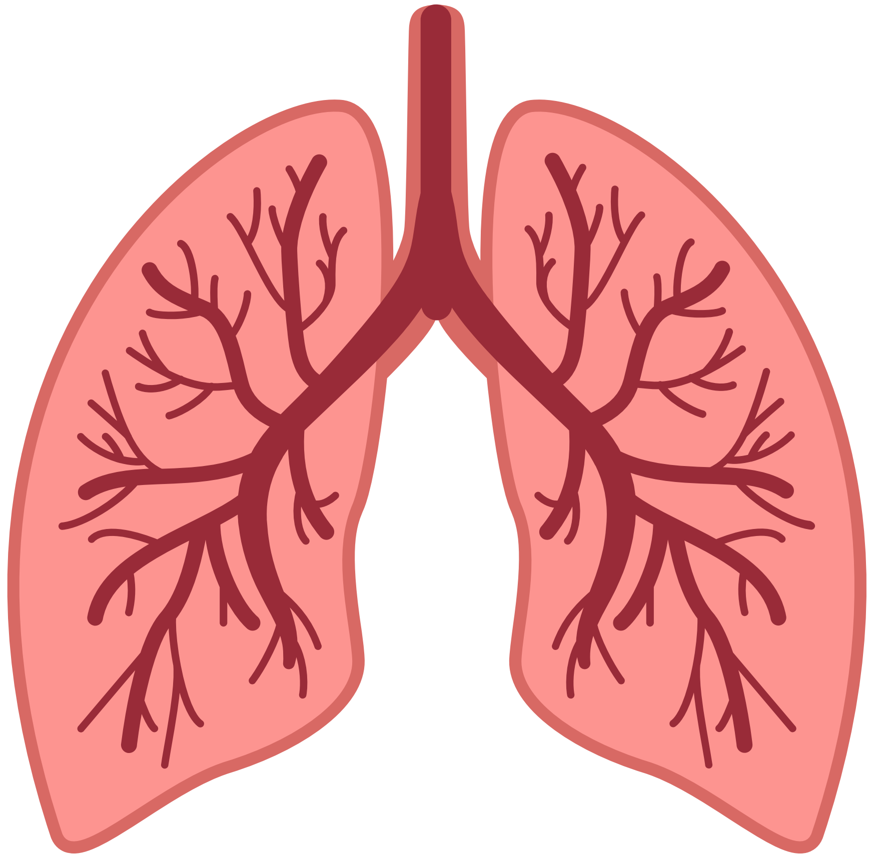
I. Introduction

LungCraft is an advanced medical imaging project focused on the analysis and visualization of lung CT scans, utilizing DICOM files to enhance diagnostic capabilities. The project aims to process and analyze 3D medical images, transforming raw imaging data into meaningful insights. By converting CT scan data into Hounsfield Units and applying image processing techniques, LungCraft enables the identification and examination of lung structures, including potential tumors. The ultimate goal is to assist in the early detection and treatment planning of lung diseases, leveraging cutting-edge visualization and data analysis methods.

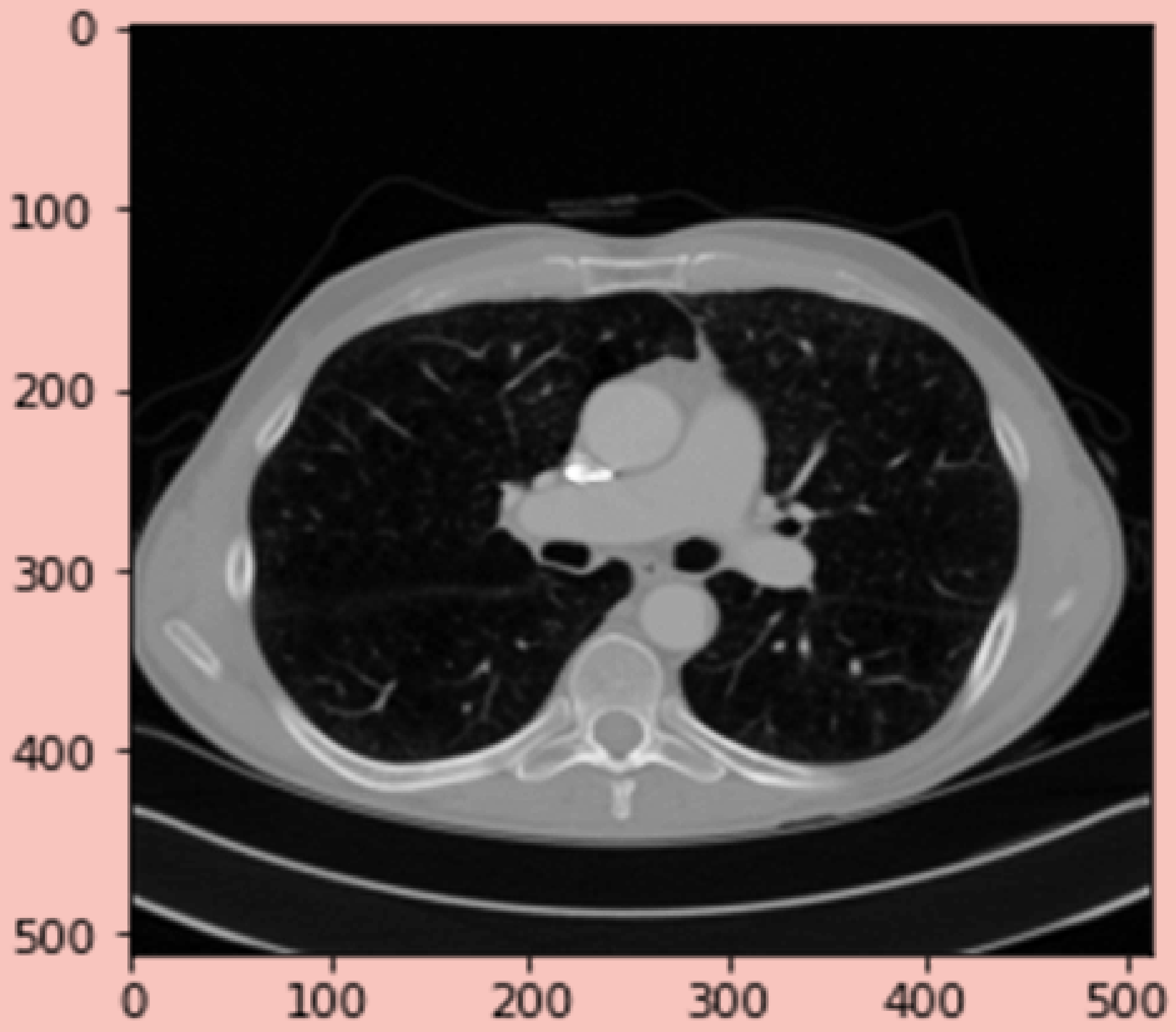


DATASET

DICOM stands for Digital Imaging and Communications in Medicine.
(It specifies a data interchange protocol, digital image format, and file structure for biomedical images and image-related information)

DICOM images contain a set of slides of images which also contain the meta data along with it.

Hounsfield Units- They are used in CT images. It is a measure of radio-density. HUs can be calculated from the pixel data with a Dicom Image.



https://www.cancerimagingarchive.net/

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Title	Data Type	Format	Access Points	Subjects	Studies	Series	Images	License
Images	CT	DICOM	DOWNLOAD (2.47GB) SEARCH Download requires NBIA Data Retriever	61	61	61	4,682	CC BY 3.0
DICOM Metadata Digest		CSV	DOWNLOAD (11.48KB)					CC BY 3.0
Representative Tumor Slices		XLS	DOWNLOAD (15.9KB)					CC BY 3.0
Clinical Data		DOC	DOWNLOAD (30.85KB)					CC BY 3.0

- The data was obtained from the Cancer Imaging Archive, specifically the LungCT-Diagnosis collection. After installing the NBIA Data Retriever, folders containing DICOM images (.dcm) files for 60 subjects (patients) were extracted.
- The data includes a metadata file, and the patients are divided into two classes: ALIVE (1) and DEAD (0). Each folder contains CT scan slides of the patients in different orientations. Applications such as QuPath and Radiant DICOM Viewer were used to view the images.

II. Literature Review

TITLE	YEAR	THEMES DISCOVERED	IDENTIFICATION OF GAPS
GENERATION OF HUMAN 3D LUNG TISSUE CULTURES (3D-LTCS) FOR DISEASE MODELING	2019	3D LUNG TISSUE CULTURES, DISEASE MODELING, ADVANCEMENTS IN 3D CELL CULTURES.	NEED FOR MORE COMPLEX MODELS TO SIMULATE VARIOUS LUNG DISEASES AND DRUG RESPONSES.
LUNG CANCER DETECTION AND CLASSIFICATION WITH 3D CONVOLUTIONAL NEURAL NETWORK (3D-CNN)	2017	3D LUNG CANCER DETECTION, CLASSIFICATION ALGORITHMS, ADVANCEMENTS IN MEDICAL IMAGING.	INTEGRATION OF MORE ROBUST MACHINE LEARNING MODELS FOR BETTER DETECTION AND CLASSIFICATION ACCURACY.
LUNG ORGANOIDS: ADVANCES IN GENERATION AND 3D-VISUALIZATION	2021	LUNG ORGANOIDS, 3D VISUALIZATION TECHNIQUES, APPLICATIONS IN DISEASE MODELING.	FURTHER ADVANCEMENTS IN 3D VISUALIZATION AND APPLICATION TO A WIDER RANGE OF LUNG CONDITIONS
PRECLINICAL VALIDATION AND IMAGING OF WNT-INDUCED REPAIR IN HUMAN 3D LUNG TISSUE CULTURES	2015	PRECLINICAL VALIDATION TECHNIQUES, IMAGING METHODS, ADVANCEMENTS IN 3D IMAGING FOR CLINICAL PURPOSES.	EXPANSION OF IMAGING TECHNIQUES TO OTHER MEDICAL FIELDS, INTEGRATION OF AI FOR ENHANCED IMAGING ANALYSIS.
A 3D CNN NETWORK WITH BERT FOR AUTOMATIC COVID-19 DIAGNOSIS FROM CT-SCAN IMAGES	2021	USE OF 3D CNNS AND BERT MODELS, AUTOMATIC DIAGNOSIS OF COVID-19, ADVANCEMENTS IN AI FOR MEDICAL APPLICATIONS.	POTENTIAL FOR COMBINING MULTIPLE AI MODELS FOR BETTER DIAGNOSIS, EXPLORATION OF ADDITIONAL DATASETS FOR VALIDATION.

II. Literature Review

TITLE	YEAR	THEMES DISCOVERED	IDENTIFICATION OF GAPS
THREE DIMENSIONAL COMPUTED TOMOGRAPHY LUNG MODELING IS USEFUL IN SIMULATION AND NAVIGATION OF LUNG CANCER SURGERY	2013	APPLICATIONS OF 3D COMPUTED TOMOGRAPHY, ADVANCEMENTS IN MEDICAL IMAGING, SPECIFIC CASE STUDIES.	INCORPORATION OF MODERN IMAGING TECHNOLOGIES, EXPLORATION OF NEW MEDICAL APPLICATIONS FOR 3D CT
THREE-DIMENSIONAL PRINTING AND 3D SLICER: POWERFUL TOOLS IN UNDERSTANDING AND TREATING STRUCTURAL LUNG DISEASE	2016	3D PRINTING IN LUNG DISEASE TREATMENT, USE OF 3D SLICER SOFTWARE, ADVANCEMENTS IN PATIENT-SPECIFIC MODELS.	FURTHER DEVELOPMENT OF PERSONALIZED MEDICINE APPROACHES USING 3D PRINTING, APPLICATION TO A BROADER RANGE OF LUNG DISEASES.
TWO-DIMENSIONAL VERSUS THREE-DIMENSIONAL CT FOR AORTIC MEASUREMENT	2003	COMPARISON OF 2D AND 3D CT SCANS, AORTIC MEASUREMENT TECHNIQUES, ACCURACY AND RELIABILITY IN MEDICAL IMAGING.	MODERNIZATION OF TECHNIQUES WITH CURRENT TECHNOLOGY, APPLICATION TO OTHER TYPES OF VASCULAR DISEASES.
3D RECONSTRUCTION OF FACE FROM 2D CT SCAN IMAGES	2011	3D RECONSTRUCTION TECHNIQUES, ALGORITHMS FOR 2D-TO-3D CONVERSION, APPLICATIONS IN MEDICAL IMAGING.	THE NEED FOR IMPROVED ACCURACY AND REAL-TIME PROCESSING, CONSIDERING ADVANCEMENTS IN AI AND MACHINE LEARNING SINCE THE PUBLICATION.
3D SEGMENTATION OF ABDOMINAL AORTA FROM CT-SCAN AND MR IMAGES	2012	SEGMENTATION ALGORITHMS, MEDICAL IMAGE PROCESSING, CHALLENGES IN ACCURATE SEGMENTATION OF COMPLEX STRUCTURES.	INCORPORATION OF NEWER DEEP LEARNING MODELS AND TECHNIQUES FOR HIGHER ACCURACY AND EFFICIENCY.

II. Literature Review

TITLE	YEAR	THEMES DISCOVERED	IDENTIFICATION OF GAPS
A NOVEL HUMAN 3D LUNG MICROTISSUE MODEL FOR NANOPARTICLE-INDUCED CELL-MATRIX ALTERATIONS	2019	3D LUNG TISSUE MODELS, NANOPARTICLE EFFECTS ON LUNG CELLS, ADVANCEMENTS IN LUNG DISEASE MODELING.	EMERGING TRENDS IN ORGANOIDS AND TISSUE ENGINEERING THAT COULD PROVIDE MORE INSIGHTS AND REFINED MODELS.
AUTOMATED IDENTIFICATION OF ANATOMICAL LANDMARKS ON 3D BONE MODELS RECONSTRUCTED FROM CT SCAN IMAGES	2009	AUTOMATED IDENTIFICATION TECHNIQUES, 3D BONE MODELING, ANATOMICAL LANDMARK DETECTION.	INTEGRATION OF MORE ADVANCED MACHINE LEARNING TECHNIQUES, AND IMPROVED PRECISION IN COMPLEX CASES.
AUTOMATIC DETECTION OF 2D AND 3D LUNG NODULES IN CHEST SPIRAL CT SCANS	2013	LUNG NODULE DETECTION, 2D VS. 3D ANALYSIS, SPIRAL CT SCAN USAGE	NEED FOR HIGHER ACCURACY AND SPEED IN DETECTION, ESPECIALLY WITH THE RISE OF AI AND DEEP LEARNING IN MEDICAL IMAGING.
COVID-19 DIAGNOSIS USING AUTOML FROM 3D CT SCANS	2021	USE OF AUTOML, 3D CT SCAN ANALYSIS FOR COVID-19, AUTOMATED DIAGNOSIS.	EXPLORATION OF MORE DIVERSE DATASETS, AND IMPROVEMENTS IN AUTOML ACCURACY AND RELIABILITY.
DEEP LEARNING FOR DIAGNOSIS OF COVID-19 USING 3D CT SCANS	2021	APPLICATION OF DEEP LEARNING, 3D CT SCANS IN COVID-19 DIAGNOSIS, AI IN HEALTHCARE.	INCORPORATION OF MORE SOPHISTICATED MODELS, AND VALIDATION WITH LARGER DATASETS.

III. Scope and Problem Statement

Scope

LungCraft focuses on developing tools for the 3D visualization and analysis of lung CT scans. The project involves processing DICOM files, converting them to Hounsfield Units, and applying image processing techniques to identify and visualize lung structures. The scope includes creating a user-friendly platform for radiologists to explore and analyze lung images, potentially extending to machine learning applications for automated diagnosis in future phases.

Problem Statement

Accurately detecting lung cancer from CT scans is challenging due to the complexity of 3D lung structures. Traditional 2D analysis can miss critical details, leading to errors or delays in diagnosis. LungCraft addresses this by enhancing 3D visualization and analysis of lung CT scans, improving the accuracy and efficiency of lung cancer detection.

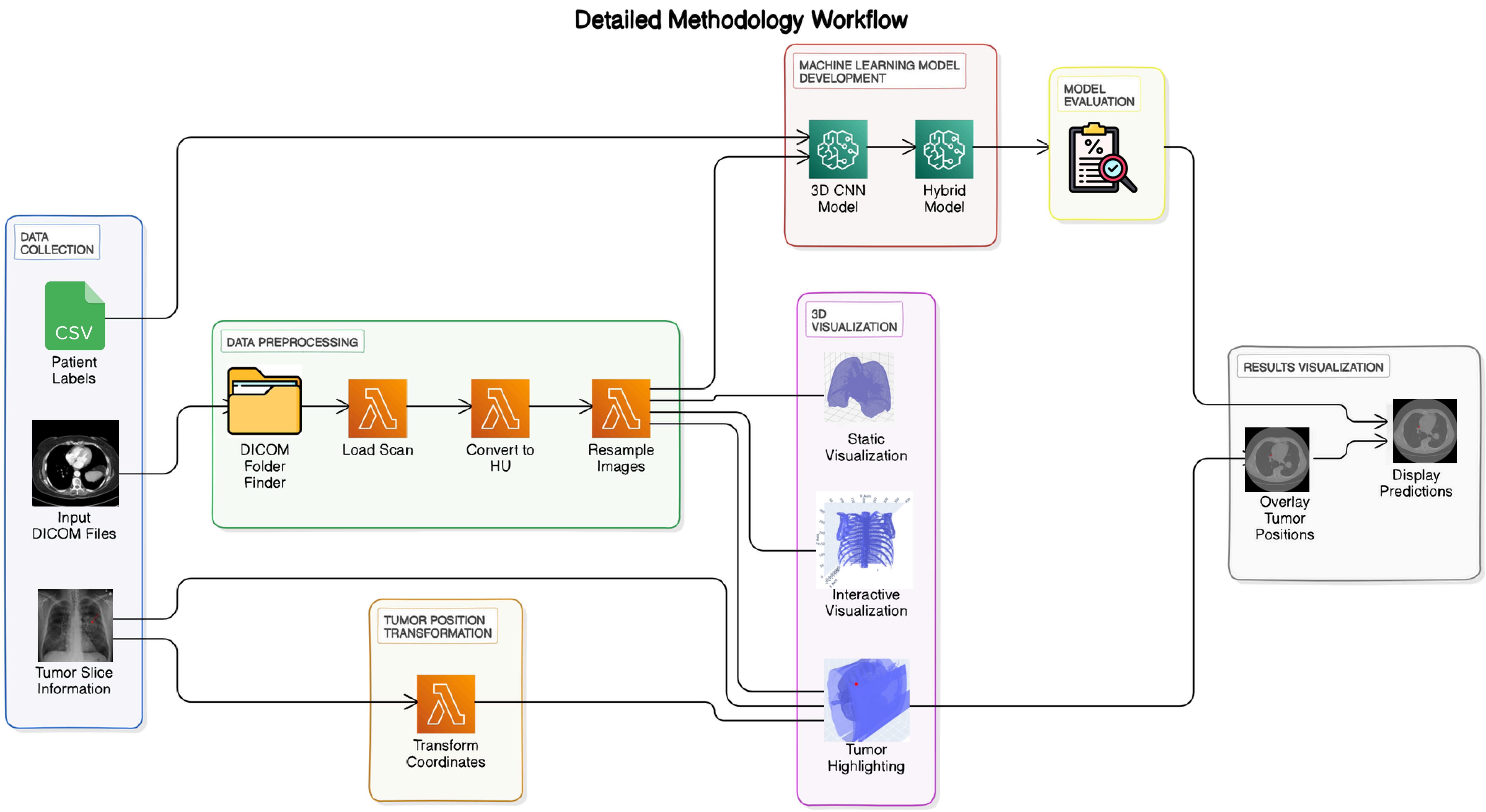
IV. RESEARCH CHALLENGES

- **Data Complexity:** Acquiring consistent, high-quality 3D lung CT data is challenging due to variations in imaging protocols and patient conditions.
- **Segmentation Accuracy:** Isolating lung tissues and tumors accurately is difficult due to anatomical variability and imaging artifacts.
- **Visualization:** Creating user-friendly 3D visualization tools that radiologists can efficiently interpret is challenging.
- **Automation and Scalability:** Automating analysis while managing large, diverse datasets is crucial for clinical application.
- **Validation:** Ensuring the accuracy and reliability of 3D models requires extensive validation with medical data.

V. Research Objective

The primary objective of LungCraft is to create various 3D models of lung structures and develop interactive tools for their visualization. Additionally, the project aims to integrate machine learning techniques for the accurate detection of lung cancer, enhancing both diagnostic precision and user interaction with the 3D models.

VI. METHODOLOGY

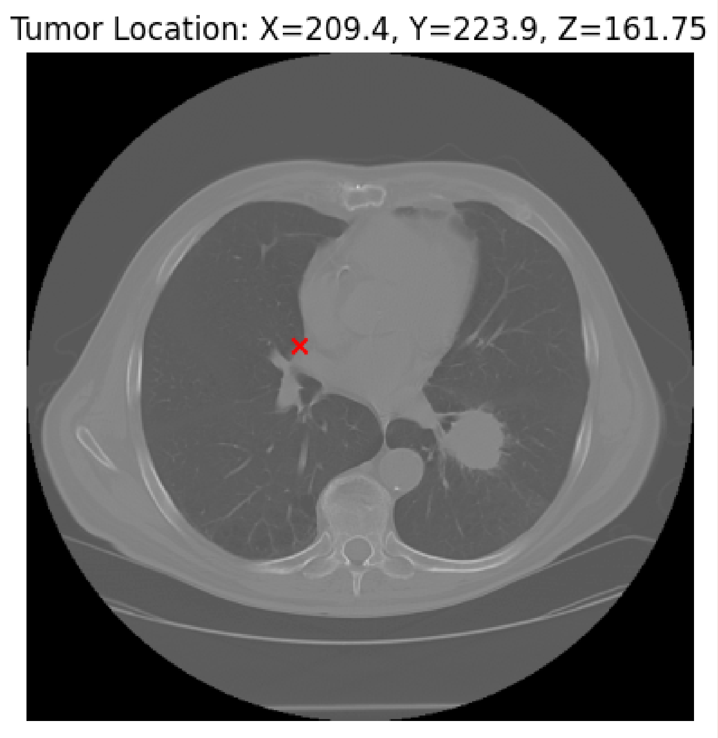


VII. RESULTS AND DISCUSSION

Previous Results:

LungCraft achieved a 92% accuracy rate in classifying CT scan data into ALIVE and DEAD categories using a 3D CNN hybrid model. This approach effectively utilized the spatial information in the CT scans, demonstrating strong predictive performance.

Both static and interactive 3D visualizations were developed, offering significant improvements over existing methods that only provided static images. The interactive model allows users to explore lung structures dynamically and integrates tumor locations directly into the 3D models. However, challenges remain with the accuracy of tumor plotting in 3D, as 2D representations are reliable while 3D visuals need refinement for precise tumor localization.

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Train on 50 samples, validate on 10 samples
Epoch 1/5
50/50 [==============================] - 140s 3s/step - loss: 0.5835 - accuracy: 0.9000 - val_loss: 2.1722 - val_accuracy: 0.7000
Epoch 2/5
50/50 [==============================] - 141s 3s/step - loss: 0.4189 - accuracy: 0.8800 - val_loss: 0.6526 - val_accuracy: 0.6000
Epoch 3/5
50/50 [==============================] - 139s 3s/step - loss: 0.3129 - accuracy: 0.8600 - val_loss: 1.2296 - val_accuracy: 0.7000
Epoch 4/5
50/50 [==============================] - 138s 3s/step - loss: 0.3226 - accuracy: 0.8800 - val_loss: 1.1120 - val_accuracy: 0.8000
Epoch 5/5
50/50 [==============================] - 139s 3s/step - loss: 0.2253 - accuracy: 0.9200 - val_loss: 1.4212 - val_accuracy: 0.8000

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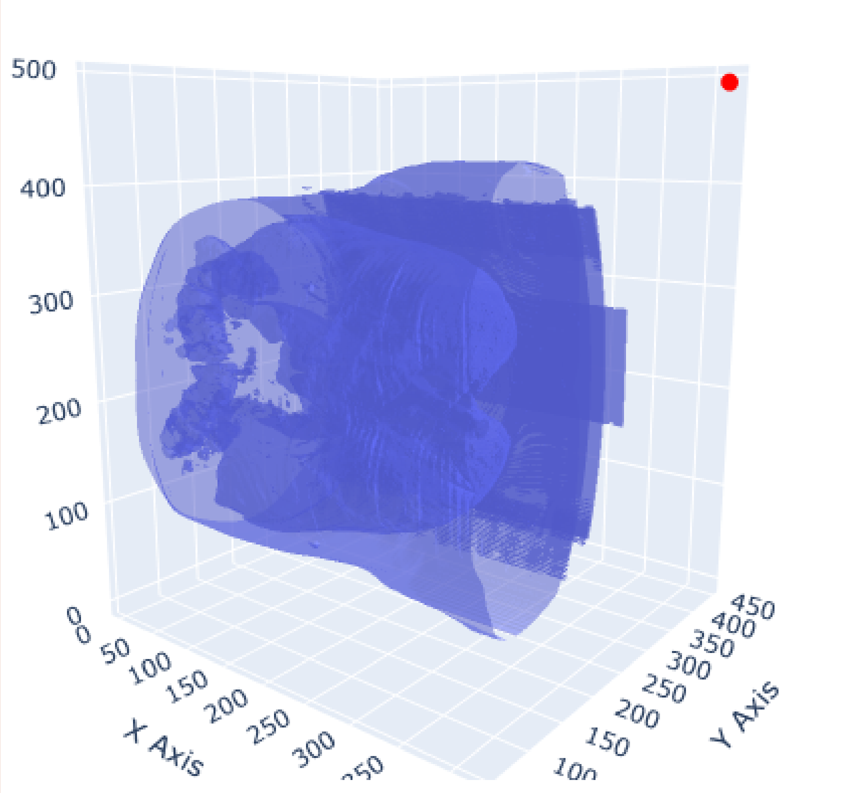
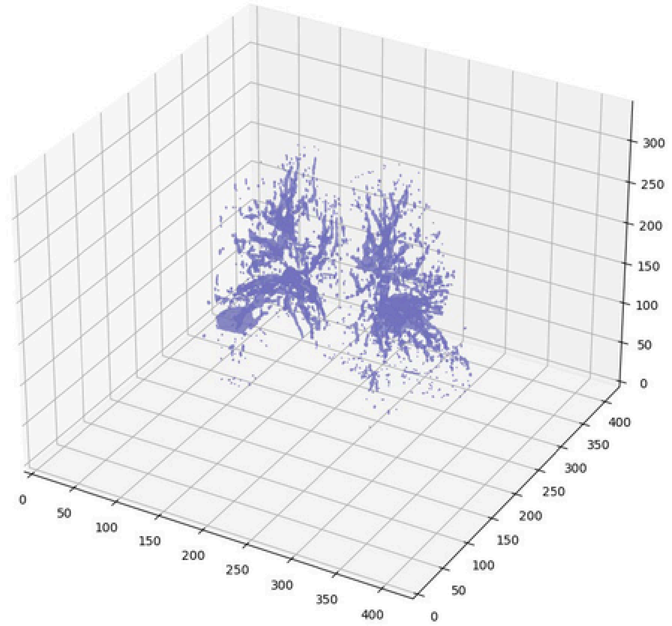
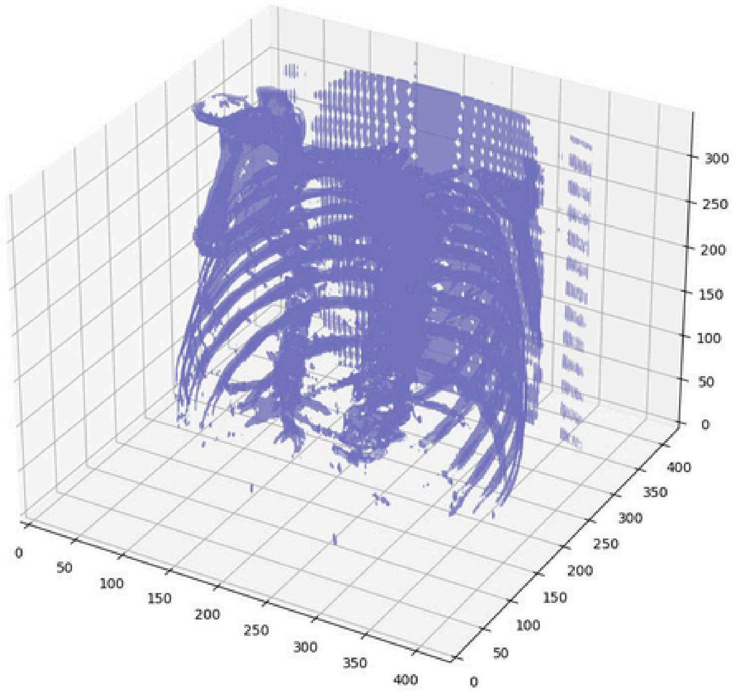


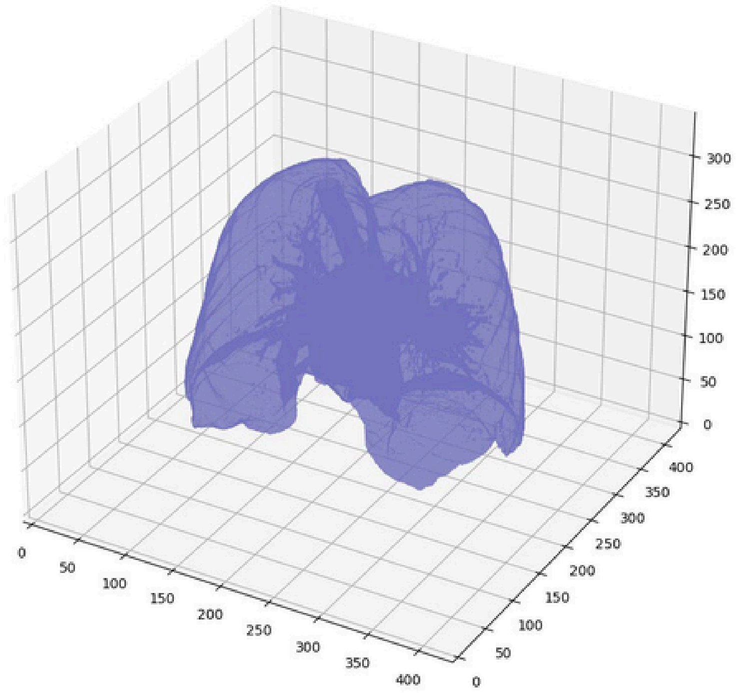
VII. RESULTS AND DISCUSSION

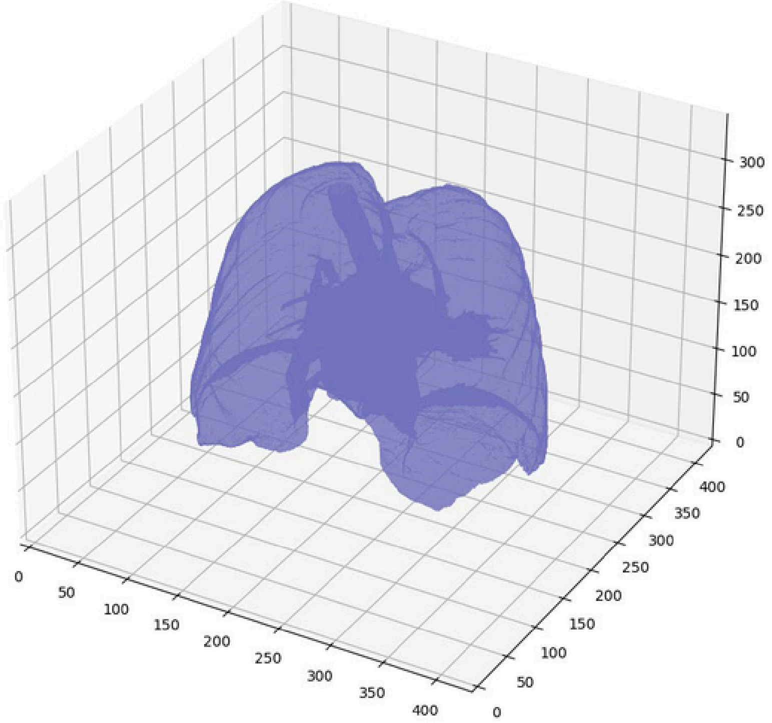
Data Processing & Visualization (2D to 3D Static):

- Successfully loaded and preprocessed CT scan DICOM files to extract Hounsfield Units, resample images, and generate clear 3D visualizations using the Marching Cubes algorithm. Visualizations included both the lung structures and segmented tumors, allowing for an interactive exploration of lung anatomy and tumor details.



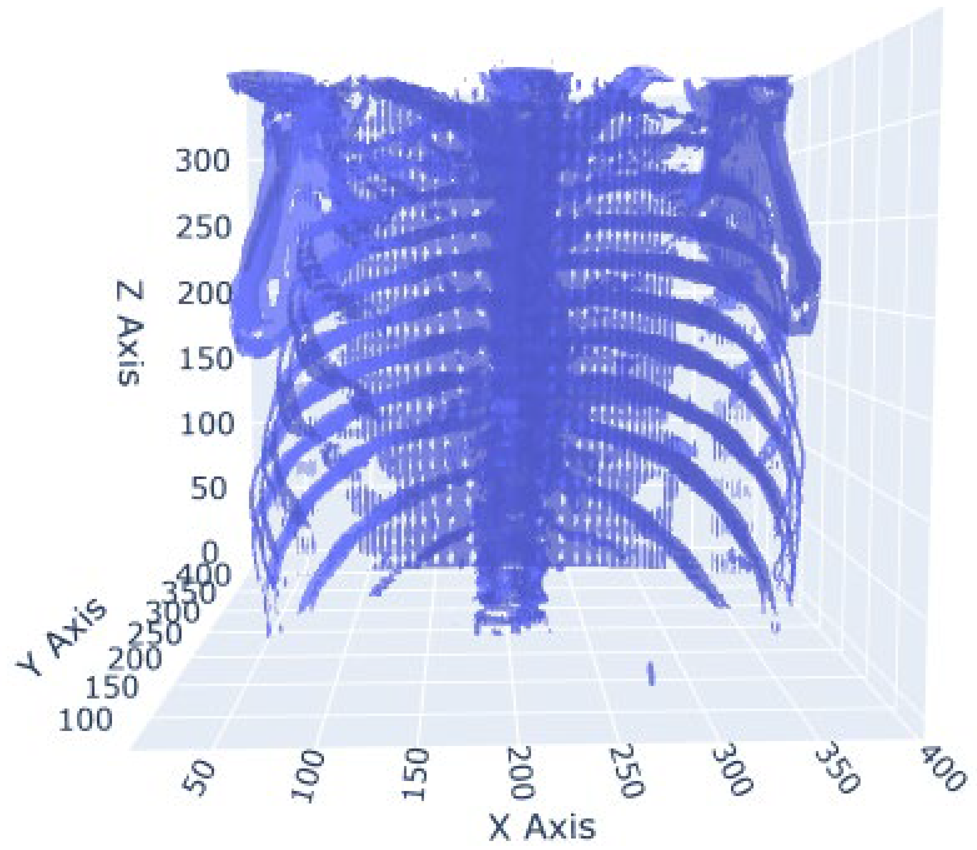






VII. RESULTS AND DISCUSSION

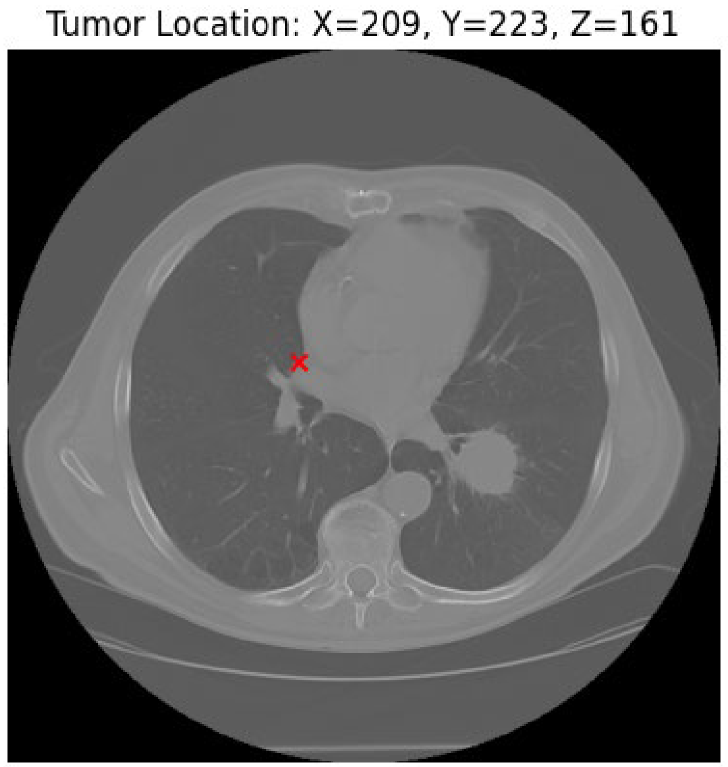
3D Static to 3D Interactive

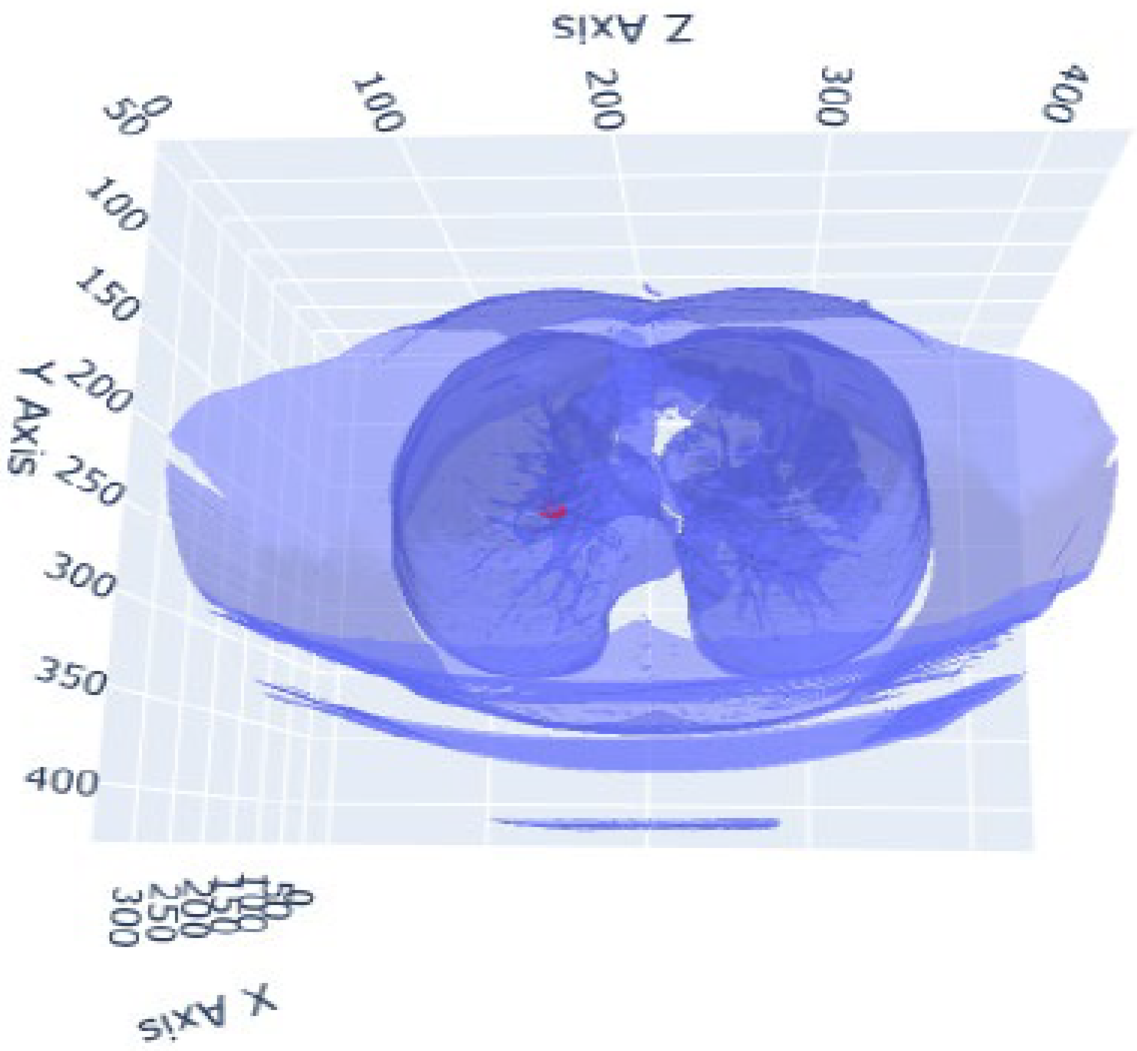


VII. RESULTS AND DISCUSSION

3D Tumor Localization:

- Mapped tumors onto the segmented 3D lung models using voxel coordinates derived from real-world measurements, enabling precise visualization of tumor positions within lung structures. This feature provides clinicians a more intuitive and detailed understanding of tumor morphology.

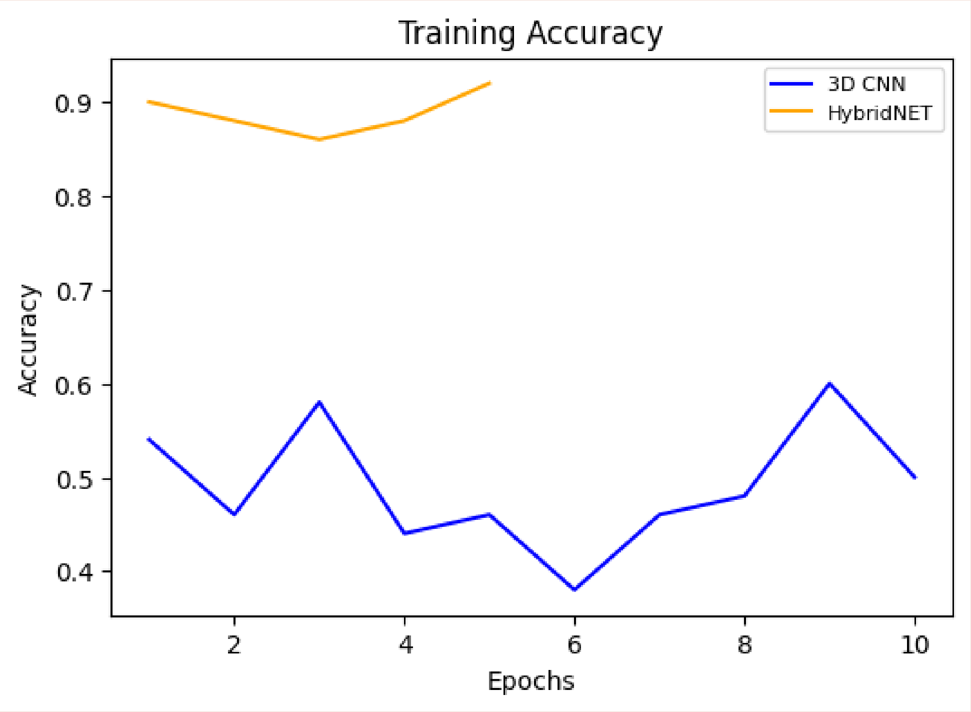




VII. RESULTS AND DISCUSSION

Machine Learning Models:

- Developed and compared a 3D CNN and a HybridNET model for lung disease classification. The HybridNET model outperformed the standard 3D CNN, achieving 92% training accuracy and 80% validation accuracy within only 5 epochs, compared to the 3D CNN's 50% training and 30% validation accuracy over 10 epochs. HybridNET demonstrated better generalization, reduced overfitting, and more stable performance on the limited dataset.

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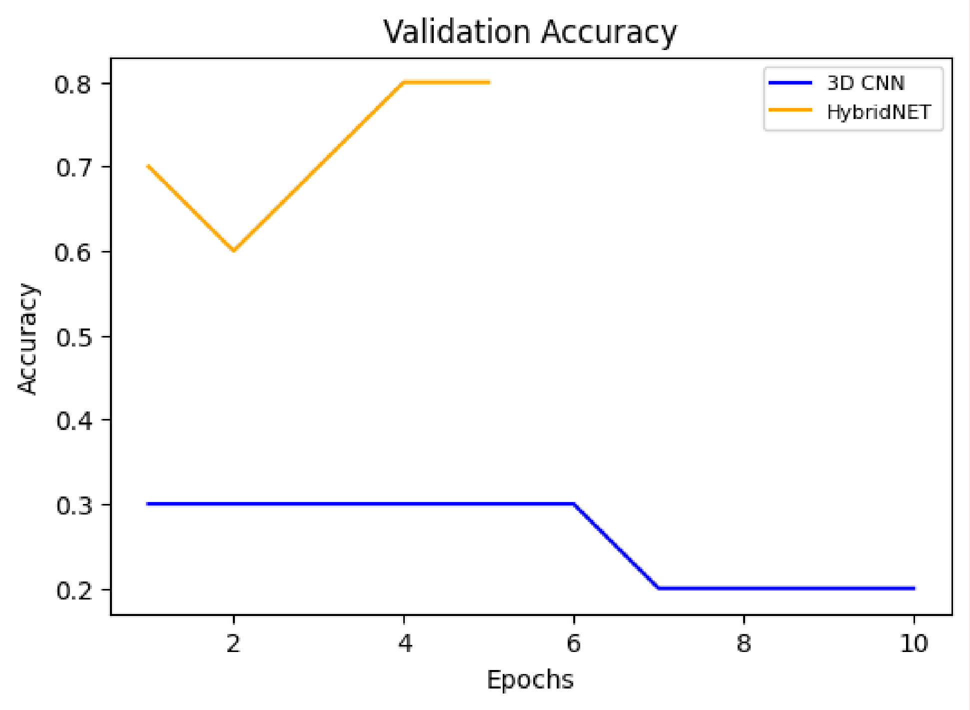
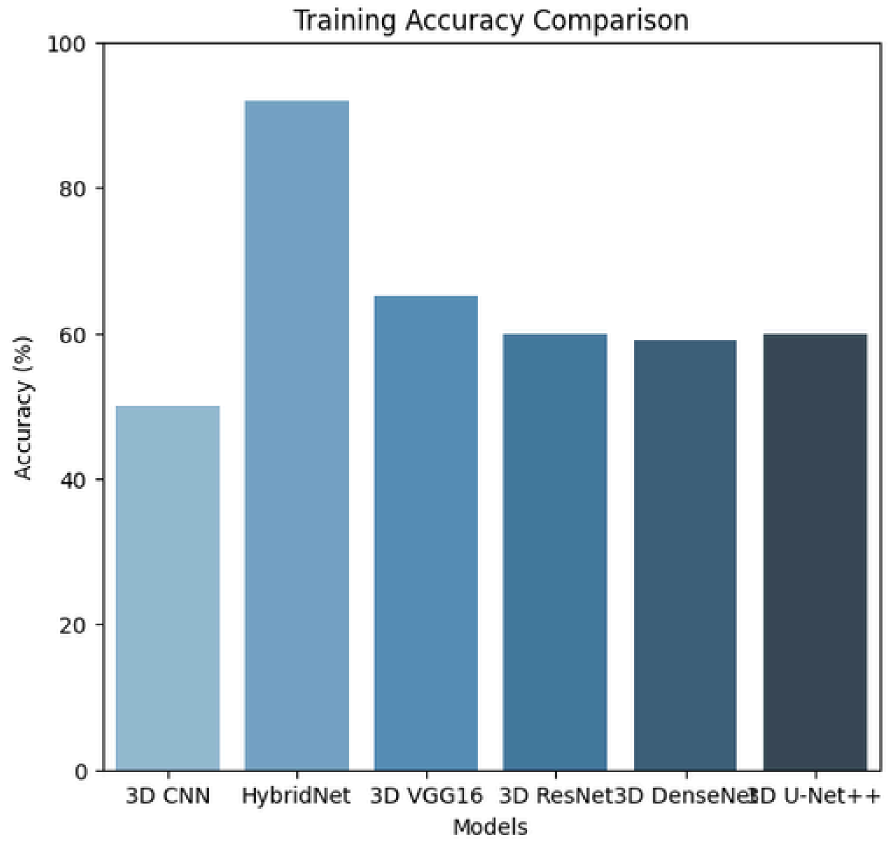
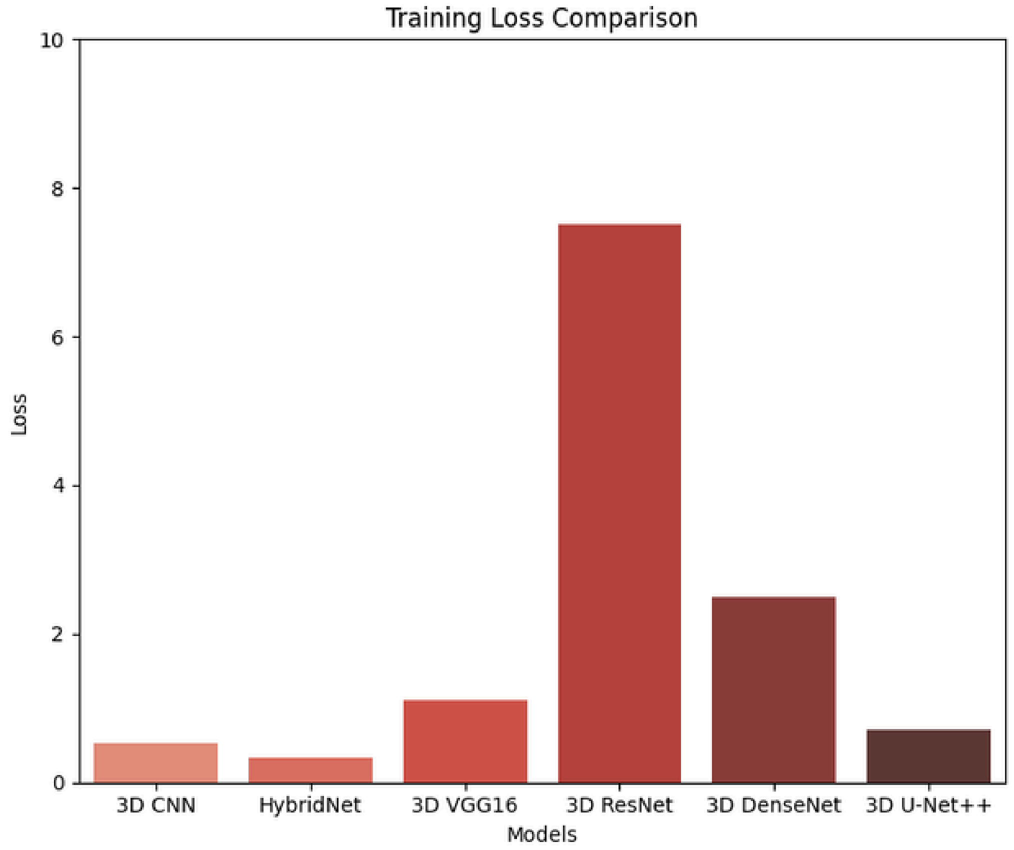


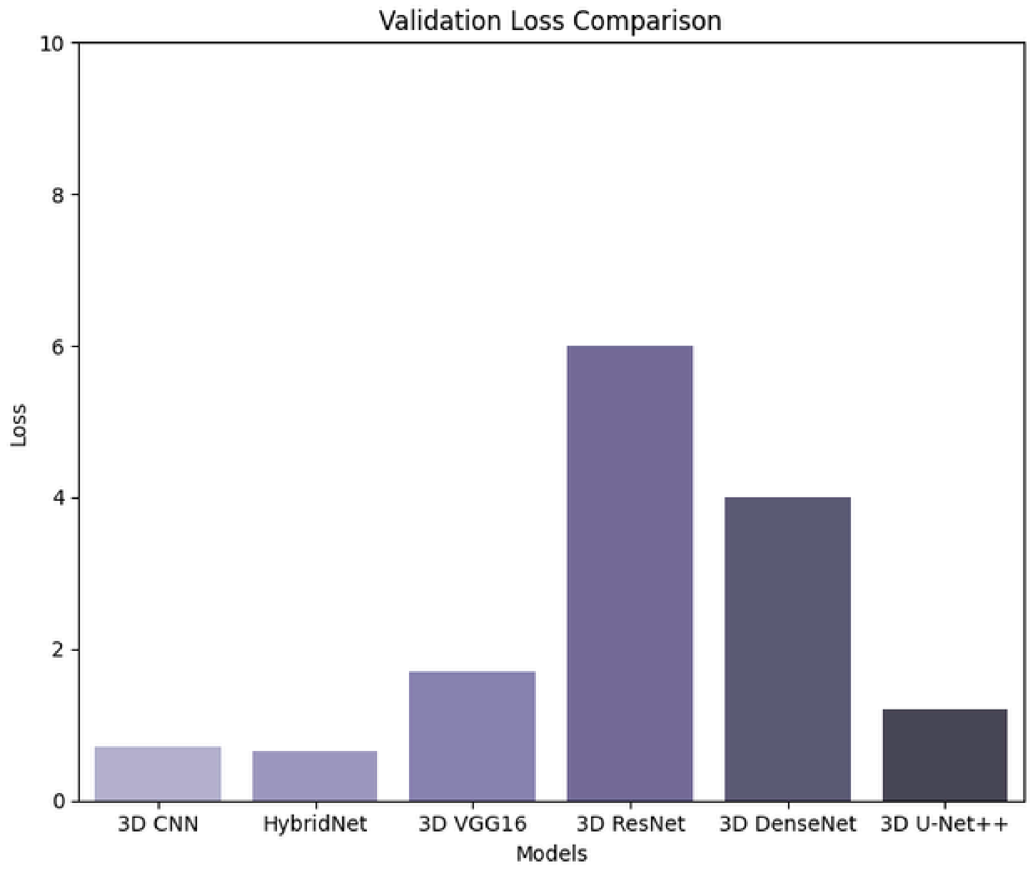
VII. RESULTS AND DISCUSSION

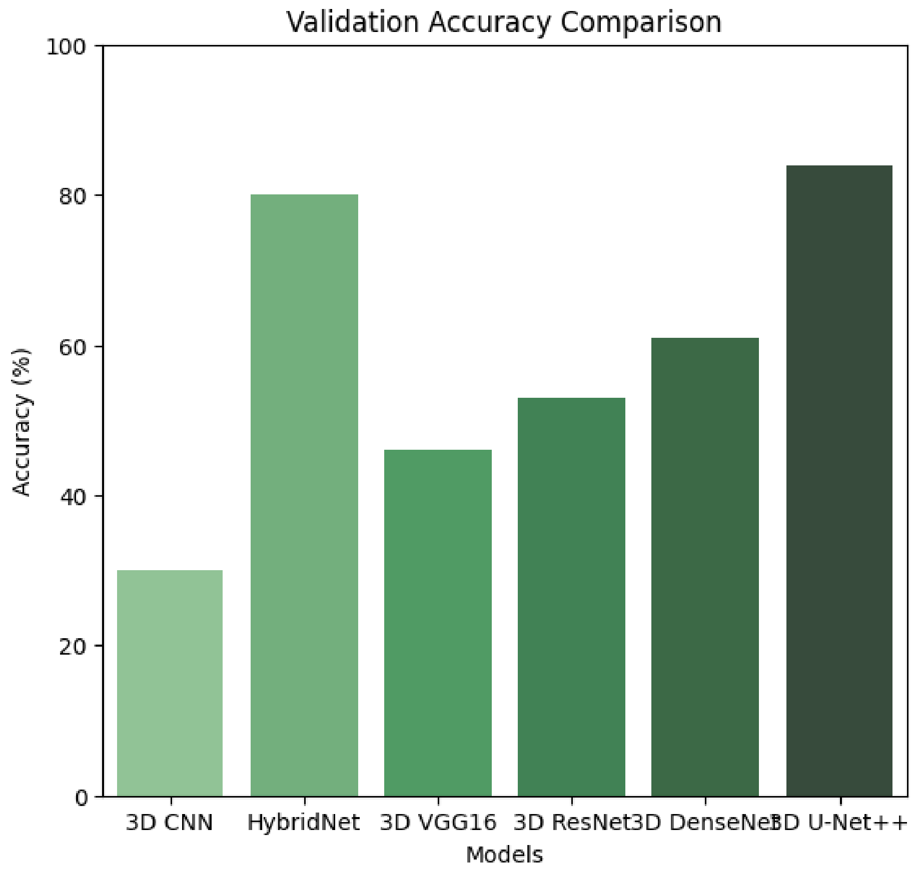
Comparative Model Performance:

- HybridNET consistently outperformed other tested 3D models, including 3D VGG16, ResNet, DenseNet, and U-Net++, in terms of both accuracy and loss. This efficiency suggests that HybridNET's hybrid approach balances the complexity of 3D data processing with computational efficiency.







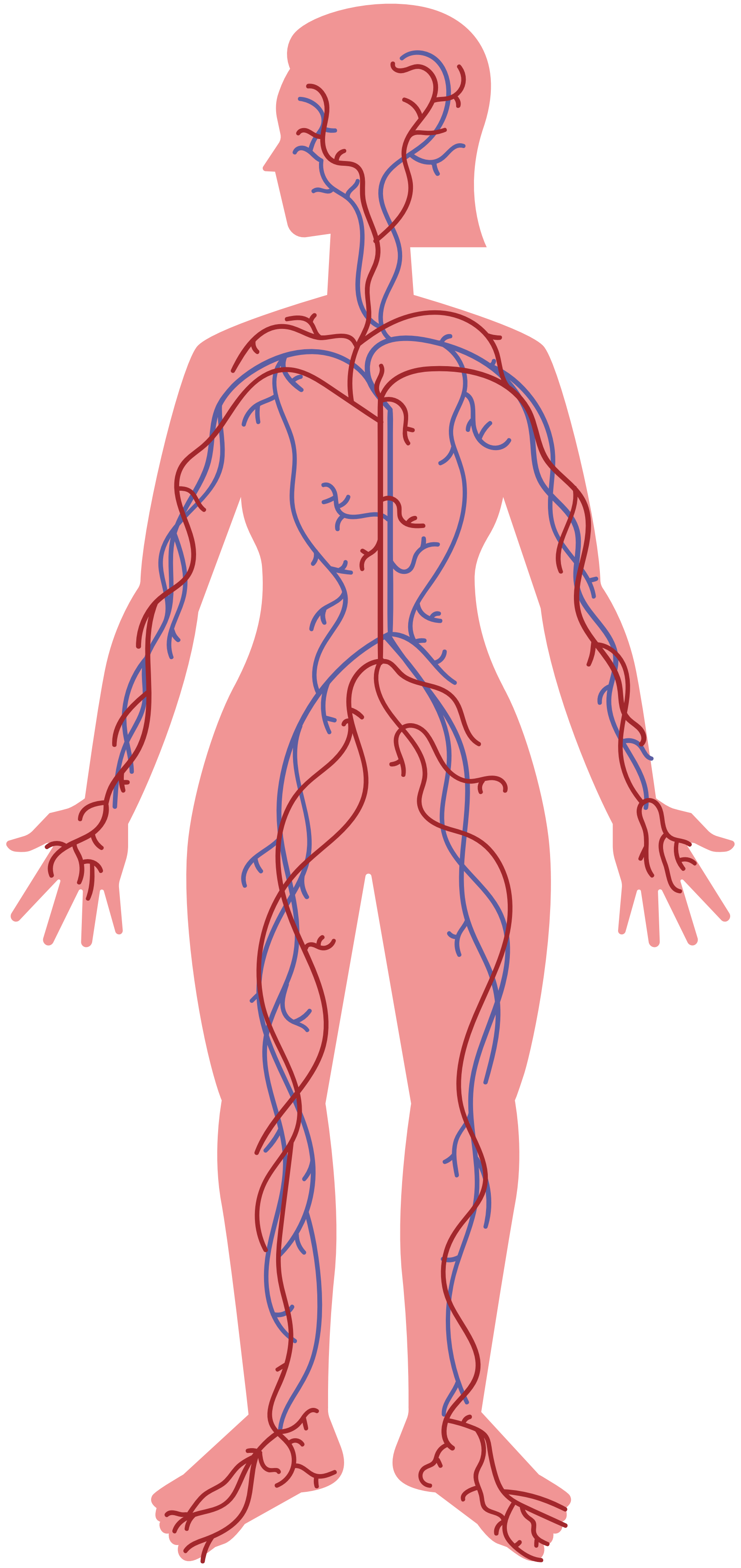


VIII. CONCLUSION

The LungCraft project demonstrates the significant potential of integrating advanced 3D visualization and machine learning for enhancing lung cancer diagnosis. By developing an end-to-end pipeline, it achieved precise lung segmentation, tumor localization, and interactive 3D visualization, providing a more comprehensive view of tumor morphology compared to conventional 2D imaging. The Marching Cubes algorithm enabled high-quality, real-time 3D models of lung structures, while precise tumor mapping allowed clinicians to explore spatial relationships within lung anatomy, potentially improving diagnostic accuracy and aiding in surgical planning.

The machine learning component, particularly the HybridNET model, proved highly effective in lung disease classification, achieving superior accuracy and generalization over alternative models like 3D CNN, VGG16, ResNet, DenseNet, and U-Net++. HybridNET's architecture, combining 3D and 2D convolutional layers, allowed it to capture critical volumetric features while maintaining computational efficiency, making it an adaptable choice for clinical settings with limited data.

Overall, LungCraft demonstrates how 3D modeling and AI can work synergistically to support clinicians in lung cancer diagnosis. With continued refinement and clinical validation, this pipeline could be integrated into healthcare workflows, improving diagnostic precision, treatment planning, and ultimately, patient outcomes in lung cancer care.



IX. Limitations and Future Work

LungCraft has shown promising results, but several limitations need addressing. One key limitation is the dataset size, which restricted the model's generalizability. While HybridNET outperformed other models on the available data, its robustness and accuracy on larger, more diverse datasets are yet to be fully tested. Additionally, 3D modeling of high-resolution CT scans requires substantial computational power, which could limit real-time application in clinical settings that lack advanced hardware. Time-consuming preprocessing and visualization steps further pose challenges for smooth integration into fast-paced healthcare workflows.

For future work, expanding LungCraft's capabilities into augmented reality (AR) or virtual reality (VR) environments could provide clinicians with an interactive, immersive way to explore 3D tumor models in real time. Implementing AR could allow real-time overlay of 3D models directly on patient images, facilitating surgery planning and in-situ decision-making. Additionally, enhancing the model's capacity to handle larger datasets and optimizing computational efficiency would improve its scalability and readiness for clinical use. Ultimately, real-world testing and validation in hospitals would ensure that LungCraft effectively supports diagnostic accuracy and treatment planning for diverse lung cancer cases.

X. GUIDE APPROVAL

XI. REFERENCES

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