*A project report on*

**LUNGCRAFT: NAVIGATING LUNGS WITH 3D DIAGNOSTICS**

*Submitted in partial fulfillment for the award of the degree of*

**M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics**

*by*

**NITHIN KODIPYAKA (20MIA1075)**



**SCHOOL OF COMPUTER SCIENCE AND ENGINEERING**

November, 2024

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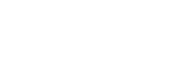
**SCHOOL OF COMPUTER SCIENCE AND ENGINEERING**

November 2024



**DECLARATION**

I hereby declare that the thesis entitled “LUNGCRAFT: NAVIGATING LUNGS WITH 3D DIAGNOSTICS” submitted by me, for the award of the degree of M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics, Vellore Institute of Technology, Chennai, is are cord of Bonafide work carried out by me under the supervision of DR. SUGANYA G.



I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

**Place: Chennai**

**Date: 10th November, 2024 Signature of the Candidate**



**School of Computer Science and Engineering**

CERTIFICATE

This is to certify that the report entitled **“LUNGCRAFT: NAVIGATING LUNGS WITH 3D DIAGNOSTICS”** is prepared and submitted by **Nithin Kodipyaka (20MIA1075)** to Vellore Institute of Technology, Chennai, in partial fulfillment of the requirement for the award of the degree of **M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics** programme is a Bonafide record carried out under my guidance. The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

Signature of the Guide:

Name: Dr. Suganya G

Date: 10th November, 2024

Signature of the Examiner 1 Signature of the Examiner 2

Name: Dr. Brindha Name: Dr. Suvidha Rupesh Kumar

Date: Date:

Approved by the Head of Department

**ABSTRACT**

LungCraft is a new application of the advanced 3D modeling and visualization techniques for computed tomography (CT) scans to better lung cancer diagnosis. In this study, a detailed dataset from The Cancer Imaging Archive will be applied by diagnostic contrast-enhanced CT scans from 61 patients diagnosed with lung adenocarcinoma. In general, the objective is to evaluate prognosis more accurately by quantitatively analyzing how image features relate to the characteristics of tumors and their outcomes in patients. The two features implemented in this work were most critical to CT: intratumor heterogeneity and tumor shape complexity, systematically scored from routinely acquired diagnostic CT images. Such features allow distinct imaging phenotypes to be recognized and are associated with highly correlated survival differences. LungCraft applies static and interactive 3D visualizations to achieve a more intuitive presentation of the morphology of tumors in the better perception of tumor behavior than the traditional techniques applied with 2D imaging. The implementation is based on a hybrid modeling approach that balances machine learning algorithms designed for the analysis of CT scans with compensation for variation in clinical image acquisition. Our results show that the quantitative imaging features are reproducible and stable, thereby revalidating their potential as valuable tools for making diagnostic decisions on lung adenocarcinoma management. This work underscores the utility of 3D imaging as an adjunct to conventional diagnostic practices and possibly transforming the approach toward evaluation and management of lung cancer in the future. Future work will include refining these techniques and clinical evaluation to determine how they can be integrated into clinical workflows.



**ACKNOWLEDGEMENT**

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**Place: Chennai**

**Date:** **Nithin Kodipyaka**

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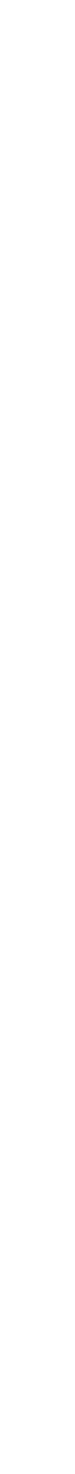
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**LIST OF ACRONYMS**

CT Computed Tomography

CNN Convolutional Neural Network

DICOM Digital Imaging and Communications in Medicine

TCIA The Cancer Imaging Archive

HU Hounsfield Units

3D Three-Dimensional

2D Two-Dimensional

**Chapter 1**

# Introduction

* 1. INTRODUCTION

Lung cancer stands as one of the leading causes of cancer-related deaths worldwide, with lung adenocarcinoma representing the most prevalent and aggressive subtype. Due to its high recurrence rate and complex growth patterns, lung adenocarcinoma presents significant challenges for early diagnosis and prognosis, critical factors for improving patient survival. Despite advancements in imaging technology, current diagnostic approaches—primarily two-dimensional (2D) computed tomography (CT) scans—fall short in capturing the intricate structural and density-based details of these tumors. The limitations inherent in 2D imaging, including a lack of spatial depth and difficulty in detecting intratumor heterogeneity, can lead to misinterpretation of tumor characteristics and suboptimal treatment decisions.

A major obstacle in diagnosing lung adenocarcinoma effectively is its morphological complexity and internal density variability. Traditional imaging techniques struggle to accurately represent these characteristics, which are crucial indicators for prognosis and therapy planning. Tumor shape complexity and density fluctuations, for example, have been associated with patient outcomes and disease progression. However, 2D CT scans provide minimal information on these dimensions, making it difficult for clinicians to evaluate the full extent of tumor aggressiveness and inform personalized treatment approaches.

This paper introduces LungCraft, an innovative framework designed to bridge these diagnostic gaps by offering three-dimensional (3D) modeling and interactive visualization capabilities for lung tumors. LungCraft leverages data from The Cancer Imaging Archive (TCIA), specifically the LungCT-Diagnosis collection, which includes CT scans from 61 patients with associated clinical metadata. This dataset enables comprehensive feature extraction, including tumor shape and density variations, providing a solid foundation for prognostic evaluation. By transforming CT scan data into high-resolution 3D models, LungCraft allows clinicians to examine tumors from multiple angles, thereby gaining deeper insights into morphological and density-based complexities that may influence clinical outcomes.

LungCraft aims to complement and extend traditional diagnostic tools by offering a dynamic and intuitive approach to lung cancer imaging, enabling improved accuracy in diagnosis and prognosis. Through interactive 3D visualization combined with quantitative feature scoring, LungCraft serves as a powerful tool for enhancing understanding of tumor behavior, potentially improving personalized treatment strategies for lung cancer patients.

* 1. CHALLENGES

Lung cancer is one of the leading causes of cancer-related deaths worldwide, accounting for more deaths than colon, breast, and prostate cancers combined. Among the different types of lung cancer, adenocarcinoma is particularly lethal due to its high recurrence rates and complex growth patterns. Early detection and precise diagnosis are crucial for improving patient survival; however, these goals are difficult to achieve with the current standard of care. While advances in imaging technology have enhanced lung cancer detection rates, accurate diagnostic methods that offer detailed insights into tumor morphology and density are still lacking. This underscores the need for innovative tools that can provide a more comprehensive understanding of lung tumors, thereby enabling personalized and effective treatment plans.

Lung cancer, particularly adenocarcinoma, presents a complex diagnostic challenge due to the high heterogeneity of tumor structures and their intricate growth patterns. Traditional diagnostic methods, primarily relying on 2D computed tomography (CT) scans, face several limitations that complicate accurate and early diagnosis:

* Limited Visualization of Tumor Complexity: Conventional 2D CT imaging restricts visualization to axial slices, making it difficult to appreciate the full spatial complexity of tumor shapes and intratumor heterogeneity. This limitation affects the ability to assess tumor boundaries, shape irregularities, and variations in density, which are critical for determining the malignancy and aggressiveness of tumors.
* Challenges in Capturing Prognostic Features: Key features, such as tumor shape complexity and density fluctuations within the tumor, are often lost in 2D imaging. Studies have shown that these features correlate with patient outcomes, but existing imaging modalities do not effectively quantify or visualize these attributes in a way that can reliably inform prognosis.
* Manual Interpretation and Inter-observer Variability: Diagnosing lung cancer through CT scans is typically a manual process that relies on radiologists’ interpretations, leading to potential inconsistencies and inter-observer variability. The lack of standardized, quantitative imaging metrics further complicates diagnosis and treatment planning, especially in early-stage detection.
* Data and Computation Limitations in 3D Modeling: Before LungCraft, attempts to use 3D imaging and machine learning for lung cancer diagnosis faced challenges related to data processing and computational load. Many models struggled to handle large 3D datasets efficiently, leading to issues in segmentation accuracy, model generalizability, and computational feasibility for real-time applications.
* Integration of Machine Learning with Clinical Imaging: Machine learning models, while promising, have been challenging to implement directly in clinical settings due to data inconsistencies, lack of interpretability, and complex computational requirements. Creating a model that integrates seamlessly with clinical imaging workflows, while providing interpretable results, has been a major barrier.

## PROJECT STATMENT

LungLung cancer remains one of the deadliest cancers worldwide, with late-stage detection significantly reducing survival rates. Despite advancements in imaging technology, current diagnostic approaches predominantly rely on 2D CT scans, which are limited in their ability to represent the complex three-dimensional structure and heterogeneity of tumors. These limitations hinder the accurate assessment of tumor morphology, intratumor heterogeneity, and spatial relationships with surrounding tissues, which are essential for precise diagnosis, staging, and prognosis.

Additionally, there is a lack of quantitative tools that can systematically score and visualize tumor features in a way that correlates with clinical outcomes. Existing diagnostic methods also lack integration with machine learning models that could aid in automated classification and risk assessment, contributing to diagnostic delays and variability across radiologists. Given the computational demands and data processing challenges associated with 3D medical imaging, developing a scalable, clinically viable solution has been difficult.

Objective: This project aims to address these gaps by developing LungCraft, a 3D modeling and visualization framework that enhances lung cancer diagnosis through interactive, quantitative analysis of CT scans. By combining interactive 3D tumor visualization with machine learning classification models, LungCraft seeks to improve the accuracy of diagnostic assessments and provide clinicians with deeper insights into tumor characteristics, ultimately supporting better patient outcomes.

## OBJECTIVES

The LungCraft project is designed with the following objectives to enhance lung cancer diagnosis using 3D modeling and machine learning:

1. Develop a 3D Reconstruction Pipeline for CT Scans: Implement an efficient pipeline to process and reconstruct lung CT scans into high-quality 3D models. This will provide clinicians with a comprehensive, interactive view of lung anatomy and tumor morphology, surpassing the limitations of 2D imaging.
2. Enable Quantitative Feature Extraction of Tumor Characteristics: Extract and quantify key prognostic features, such as tumor shape complexity and intratumor heterogeneity, from CT images. These features will help in understanding tumor aggression and correlating imaging phenotypes with patient outcomes.
3. Implement Advanced Machine Learning Models for Tumor Classification: Integrate machine learning models, including a hybrid 3D CNN and 2D convolution architecture (HybridNET), to classify lung CT scans and predict tumor presence and characteristics. This component aims to automate the diagnostic process and improve classification accuracy.
4. Enhance Diagnostic Visualization Through Interactive 3D Modeling: Incorporate interactive 3D visualization tools that allow clinicians to manipulate and analyze tumor models dynamically, facilitating a more intuitive assessment of tumor behavior and spatial relationships within the lung.
5. Ensure Clinical Feasibility and Efficiency: Optimize the LungCraft pipeline to minimize computational load, improve processing speeds, and ensure scalability for clinical applications. This objective focuses on creating a solution that can be feasibly integrated into clinical workflows without compromising performance.

## SCOPE OF THE PROJECT

The LungCraft project is designed to address critical limitations in lung cancer diagnosis by integrating advanced 3D imaging and machine learning capabilities within a unified framework. The project involves developing a comprehensive pipeline for processing and reconstructing CT scan data into detailed 3D models, specifically focused on visualizing lung anatomy and tumor morphology. By standardizing image data across varying acquisition protocols and resolutions, LungCraft ensures consistency in 3D reconstructions, enabling an accurate representation of anatomical structures within the lungs.

This project further aims to provide quantitative imaging insights through the extraction of key tumor features, including shape complexity and intratumor heterogeneity, which are significant for prognostic evaluations. These quantitative metrics, derived from high-resolution 3D models, enhance traditional diagnostic approaches by offering deeper insights into tumor characteristics that correlate with patient outcomes. Additionally, LungCraft incorporates machine learning models, including a hybrid 3D CNN architecture, to automate the classification of lung cancer presence and severity based on these imaging phenotypes. This integration of 3D visualization and predictive analytics aims to streamline diagnostic workflows and reduce inter-observer variability, offering a more robust and standardized tool for lung cancer assessment.

LungCraft is ultimately designed with clinical application in mind, balancing computational efficiency with diagnostic effectiveness to facilitate smooth integration into real-world healthcare environments. The project focuses on creating a practical and scalable solution that can support radiologists and oncologists in making more accurate and timely diagnoses, potentially improving treatment planning and patient outcomes in lung cancer care.

**Chapter 2**

# Related Work

Gerckens et al. (2019) developed 3D lung tissue cultures (3D- LTCs) from precision-cut lung slices (PCLS) to model human lung diseases more effectively. Their work emphasizes the importance of preserving tissue architecture, biomechanics, and cellular diversity to closely resemble in situ lung conditions. The 3D-LTCs enable detailed analysis of drug responses and disease mechanisms, particularly in fibrosis research, offering personalized insights through patient- derived tissue. While their focus lies on ex vivo modeling for biochemical studies, our research diverges by using non- invasive CT-based 3D models to visualize tumor structures and predict patient outcomes. Both studies contribute to advancing personalized medicine, with Gerckens et al. providing tissue-level insights and our work focusing on diagnostic imaging for improved lung cancer prognosis [1].

Alakwaa et al. (2017) introduced a computer-aided diagnosis (CAD) system leveraging 3D convolutional neural networks (3D-CNNs) for lung cancer detection using CT scans. Their approach focuses on automating the segmentation, detection, and classification processes by integrating a modified U-Net and 3D-CNNs. Although the use of deep learning in their work yields a high classification accuracy of 86.6%, it also highlights the challenges of false positives during nodule detection. While their research centers on the application of machine learning models to automate cancer diagnosis, our work shifts toward enhancing diagnostic visualization through interactive 3D models of CT scans. Both studies aim to improve lung cancer management, but ours focuses on combining imaging phenotypes and survival analysis to offer a more interpretable, non-invasive approach for clinical applications [2].

Cunniff et al. (2021) explored the development and visualization of lung organoids, emphasizing the importance of maintaining the 3D architecture of lung tissue for accurate biological modeling. Their work highlights how conventional 2D culture systems fail to capture the complexity of lung structures, which is essential for understanding disease mechanisms. By leveraging high-resolution microscopy, they demonstrate how lung organoids can replicate in vivo conditions, offering insights into both healthy and diseased states of the lung. While their research focuses on 3D tissue cultures for experimental manipulation, our study extends the idea of 3D modeling by applying it directly to diagnostic CT scans, enabling clinicians to visualize tumor heterogeneity and shape complexity interactively. Both efforts underscore the critical role of 3D visualization in advancing lung disease research and treatment strategies [3].

Uhl et al. (2015) developed and validated patient-derived 3D lung tissue cultures (LTCs) to investigate Wnt/β-catenin signaling for lung tissue repair, focusing on chronic obstructive pulmonary disease (COPD). Their work emphasizes the importance of mimicking the native lung microenvironment through 3D models, which allow for detailed molecular analysis and high-resolution imaging. They demonstrated the activation of Wnt/β-catenin signaling pathways in patient-derived tissues, showing promising therapeutic potential through enhanced epithelial cell regeneration and reduced tissue degradation. While their study focuses on preclinical therapeutic validation for COPD, it aligns with our work’s goal of leveraging 3D visualization for diagnostic and therapeutic advancements. Both approaches highlight the utility of 3D models in advancing personalized healthcare by closely replicating patient- specific lung environments [4].

Tan and Liu (2021) introduced a novel framework that combines 3D CNNs with BERT for the automatic diagnosis of COVID-19 from CT scan images. Their approach involves preprocessing CT slices by segmenting lung regions and filtering out irrelevant backgrounds. A resampling method ensures consistent input size by selecting a fixed number of slice images for training and validation. The framework uses a 3D CNN to extract spatial features, integrated with BERT to enhance contextual understanding of the images. The extracted features are aggregated into a feature vector and fed into a multi-layer perceptron (MLP) for final classification. Their model achieved high performance, with an F1 score of 0.9261 on validation and 0.8822 on test datasets. This work demonstrates the effectiveness of combining deep learning models with language models for image-based medical diagnosis, which aligns with our use of 3D data but emphasizes COVID-19 detection. The framework showcases the potential of 3D models for diagnostic applications, further motivating our exploration of 3D visualization for lung cancer analysis [5].

Ikeda et al. (2013) highlighted the value of three-dimensional (3D) computed tomography (CT) lung modeling in enhancing the precision and safety of lung cancer surgeries. With the rise of minimally invasive procedures, such as video-assisted thoracoscopic surgery (VATS) lobectomy and segmentectomy, understanding the complex anatomy of pulmonary vessels and bronchi is critical for successful operations. The use of multi-detector CT (MDCT) allows surgeons to generate detailed 3D images of lung structures, enabling preoperative simulations and real-time navigation during surgery. This technology provides surgeons with a comprehensive view of vascular and bronchial pathways, enhancing both the accuracy of dissections and patient safety. Advances in imaging software have further improved the visualization of small vessels, supporting more precise segmentectomy procedures. Ikeda et al. emphasize that 3D modeling not only facilitates safer surgeries but also serves as a valuable tool for training junior surgeons and boosting operator confidence. This approach aligns with our focus on leveraging 3D visualization to provide more detailed insights into lung structures, reinforcing the potential for improved medical interventions through advanced modeling techniques [6].

Cheng et al. (2016) explored the transformative impact of three-dimensional (3D) printing and 3D slicer technology in understanding and treating structural lung diseases. As the 3D printing industry advances, clinicians have begun to leverage these technologies for various applications, including pre- procedural planning, biomedical tissue modeling, and the production of custom implantable devices. However, the authors note that despite the growing adoption of rapid prototyping and additive manufacturing techniques in healthcare, many physicians still lack the necessary technical skills to utilize these innovative tools effectively. They discuss the rapid growth of the 3D printing sector, which introduces a multitude of 3D printers and materials, emphasizing the need for clinicians to remain informed about these developments to fully exploit their potential benefits. The paper reviews the history of 3D printing and its recent biomedical applications while addressing the significant barriers to its widespread adoption in the medical field. Cheng et al. also provide a guide for clinicians on designing personalized airway prostheses using 3D Slicer, aiming to facilitate greater participation in the 3D printing sector. This work underscores the importance of integrating advanced technologies into clinical practice, aligning with our objective of enhancing lung cancer diagnosis through innovative modeling and visualization techniques [7].

Dillavou et al. (2003) conducted a study to evaluate the accuracy of aortic diameter measurements using two- dimensional (2D) versus three-dimensional (3D) computed tomography (CT) scans. The research involved two independent, blinded observers who measured the aortic neck and sac diameters from 40 2.5-mm 2D CT scans of 31 patients using electronic calipers and a circular tool for 3D reconstructions. The measurements were obtained at specified anatomical landmarks, with data analyzed through intraclass correlation coefficients (ICC), Bland-Altman variation assessments, and absolute differences. The results indicated a high correlation between 2D minor axis measurements and 3D measurements, with the ICC values for the neck and sac demonstrating strong reliability (neck ICC = 0.9282; sac ICC = 0.8956). While the correlation for the major axis was lower, the average absolute difference between 3D and 2D minor axis diameters was just 1.01 mm, compared to 2.61 mm for the major axis. The authors concluded that minor axis measurements derived from 2D scans are generally sufficient for clinical applications, suggesting that 3D reconstructions may not be necessary for routine aortic diameter assessments. This study highlights the potential for simpler imaging techniques in clinical practice while also setting a foundation for the exploration of more advanced imaging methods, such as 3D modeling, in lung cancer diagnosis [8].

Kumar and Vijai (2012) discuss advancements in 3D reconstruction techniques of the human face from 2D CT scan images, emphasizing their applications in craniofacial surgery. The authors propose a software tool designed to aid surgeons in planning and executing facial reconstruction procedures. They analyze various existing approaches for 3D reconstruction, which range from applications in visualizing real-world scenarios to modeling anatomical structures. The paper evaluates different algorithms, highlighting their suitability for reconstructing various regions of the face, including soft tissues and hard bones. The survey concludes by assessing the effectiveness of each method and recommending the most appropriate approaches for specific medical applications, underscoring the importance of precise modeling in improving surgical outcomes. This work contributes to the growing field of 3D imaging and modeling in medicine, which has significant implications for surgical planning and patient care [9].

Duquette et al. (2012) developed a semi-automatic method for 3D segmentation of the abdominal aorta, focusing on the aneurismal sac of abdominal aortic aneurysms (AAAs) from both CT and MR images. Utilizing graph cut theory, the method minimizes human intervention while effectively segmenting the lumen interface and aortic wall. Tested on a dataset of 44 patients and 10 synthetic images, the segmentation results were compared to manual tracings from four experts, demonstrating that the semi-automatic method achieved similar variability to human operators. This approach provides reliable and reproducible evaluations of the abdominal aorta, enhancing diagnostic accuracy and treatment planning for AAAs [10].

Kabadi et al. (2019) developed a novel 3D lung microtissue model to study nanoparticle-induced alterations in cell- matrix interactions, particularly focusing on multi-walled carbon nanotubes (MWCNTs). Traditional toxicity testing methods rely heavily on 2D in vitro assays and in vivo animal studies, which often yield conflicting results. In contrast, this study co-cultured human lung fibroblasts and epithelial cells with macrophages to form scaffold-free 3D microtissues, which more accurately mimic human physiology. After exposing these microtissues to MWCNTs, carbon black nanoparticles, and crocidolite asbestos fibers, the researchers evaluated microtissue viability, morphology, and gene expression associated with inflammation and extracellular matrix remodeling. The findings indicate that 3D lung microtissues can effectively predict chronic pulmonary endpoints and provide a more relevant alternative for nanomaterial toxicity testing, enhancing understanding of toxicity pathways and potential health hazards from nanoparticle exposure [11].

Subburaj, Ravi, and Agarwal (2009) present a novel computer graphics-based method for the automated identification of anatomical landmarks on 3D bone models reconstructed from CT scan images. The accurate localization of these landmarks is critical for patient-specific preoperative planning, such as tumor referencing and implant alignment, as well as for intra-operative navigation. The authors’ method segments the bone model's surface into different landmark regions—peak, ridge, pit, and ravine—based on surface curvature, and employs an iterative process using a spatial adjacency relationship matrix to label these regions automatically. The performance of the automated system was evaluated against manual landmark identification by three experienced orthopedic surgeons on three 3D bone models, revealing variability in landmark location ranging from 2.15–5.98 mm for the manual method and 1.92–4.88 mm for the automated approach. The results indicate that the automated methodology performed comparably or better than manual identification, demonstrating reproducibility and potential for various applications in surgical planning and navigation [12].

El-Baz et al. (2013) present a novel algorithm for the automatic detection of lung nodules in chest spiral low-dose CT (LDCT) scans, addressing a significant challenge in the computer analysis of chest radiographs. The proposed method involves three main steps: first, it isolates lung nodules, arteries, veins, bronchi, and bronchioles from surrounding anatomical structures. The second step utilizes deformable 2D and 3D templates that characterize the typical geometry and gray-level distribution of lung nodules for detection. This detection process combines normalized cross- correlation template matching with a genetic optimization algorithm to enhance accuracy. In the final step, the algorithm reduces false positives by applying three robust features to distinguish true lung nodules. Testing on 200 CT datasets demonstrates that the proposed algorithm achieves results comparable to those of expert radiologists, highlighting its potential utility in clinical practice for improving lung nodule detection accuracy [13].

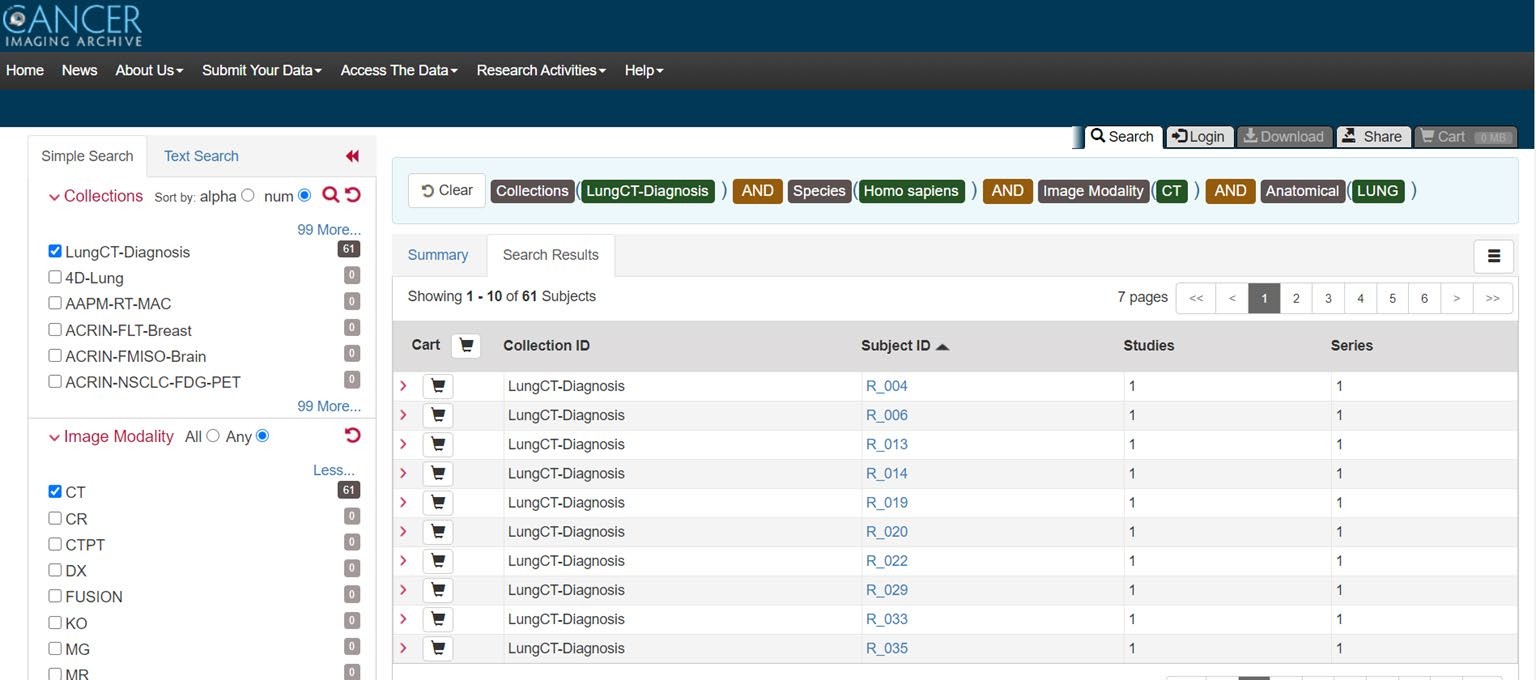
Anwar (2021) discusses an innovative approach to diagnosing COVID-19 using AutoML techniques applied to 3D CT scans. The study highlights the limitations of polymerase chain reaction (PCR) tests, which have a high false-negative rate, necessitating alternative diagnostic methods. CT scans provide detailed insights into the chest but typically involve analyzing hundreds of slices, making manual diagnosis by radiologists and pulmonologists time- consuming. To address this, the author proposes an automated AI-based method that leverages AutoML for efficient diagnosis. The model is trained on 2D slices of CT scans rather than 3D scans, with predictions aggregated to label the overall 3D CT scan based on the most frequently occurring diagnosis among the slices. By employing different thresholds, the model classifies scans as COVID-positive or negative. The approach achieved an impressive accuracy of 89% and an F1-score of 88%, demonstrating its potential as a reliable diagnostic tool. The implementation is publicly available, contributing to further research and application in the clinical setting [14]

Serte and Demirel (2021) present a deep learning approach for diagnosing COVID-19 using 3D CT scans, addressing the urgent need for efficient detection methods in hospitals. With the rapid spread of COVID-19 and its associated mortality, timely isolation of infected individuals is crucial. CT scans serve as valuable diagnostic tools, but the extensive number of slices in each scan can cause delays in diagnosis. To overcome this challenge, the authors propose an AI-based methodology utilizing the ResNet-50 deep learning model to classify CT images as either COVID-19 positive or normal. The model processes individual images from the 3D CT scans and aggregates these image-level predictions to provide a comprehensive diagnosis for the entire volume. The results indicate that this deep learning approach achieves an impressive area under the curve (AUC) value of 96%, demonstrating its potential effectiveness in rapid and accurate detection of COVID-19 from CT imaging [15].

**Chapter 3**

# Dataset

In this study, we utilized a comprehensive dataset from The Cancer Imaging Archive (TCIA), as illustrated in Fig. 1. The dataset specifically comprises the LungCT-Diagnosis collection, a well-curated repository of diagnostic, contrast-enhanced CT scans of lung adenocarcinoma patients. This dataset underpins the development and evaluation of our AI-driven diagnostic tools, facilitating in-depth analysis of lung tumors for improved prognostic accuracy.



*Figure 1 LungCT-Diagnosis dataset from Cancer Imaging Archive.*

## DATA OVERVIEW

Title: Quantitative Computed Tomographic Descriptors Associate Tumor Shape Complexity and Intratumor Heterogeneity with Prognosis in Lung Adenocarcinoma

DOI: 10.7937/K9/TCIA.2015.A6V7JIWX

Location: Lung

Species: Human

Subjects: 61 patients

Data Types: CT images and supporting clinical data

Cancer Types: Lung Cancer

Size: 2.47 GB

Status: Public, Complete

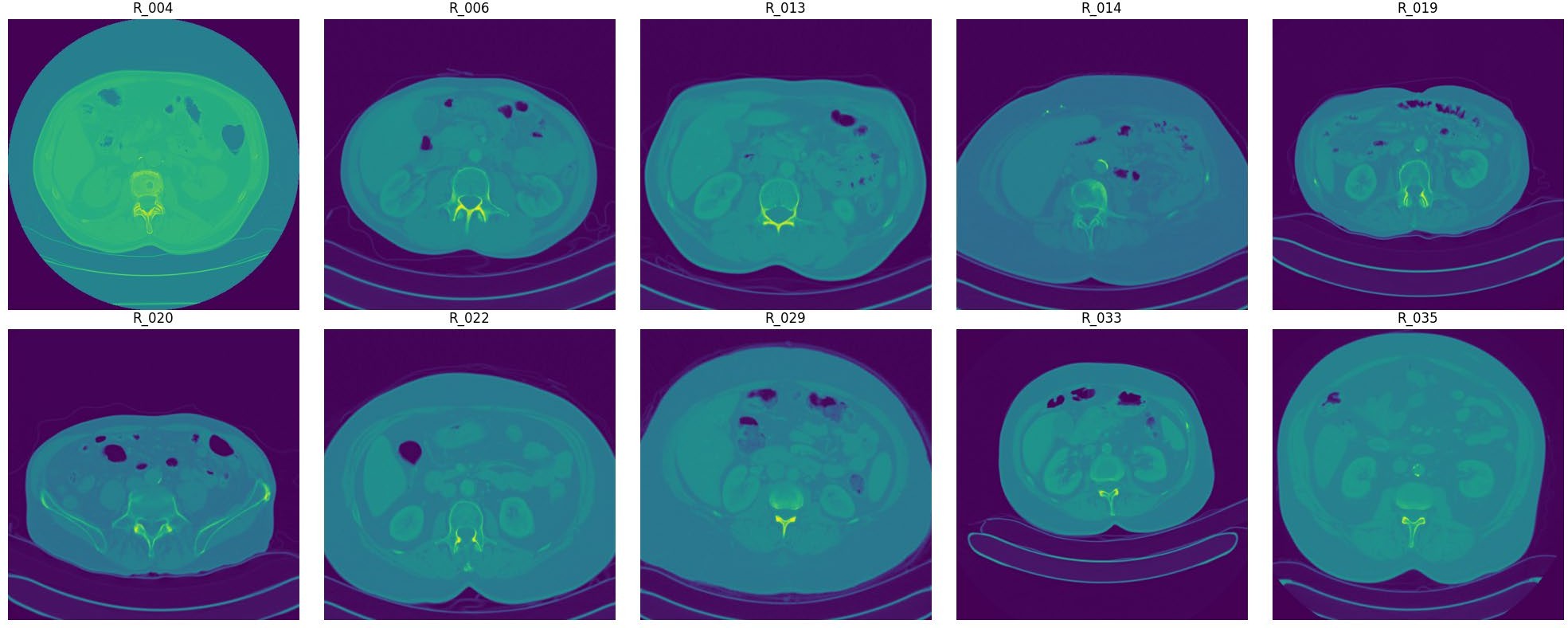
This dataset serves as a valuable resource for extracting imaging biomarkers related to tumor morphology and density variation. As lung adenocarcinoma has unique structural and density characteristics that correlate with prognosis, this data enables the development of robust, quantitative tools for tumor analysis and survival prediction.

## DATASET SUMMARY

The **LungCT-Diagnosis collection** contains a total of 4,682 diagnostic contrast-enhanced CT images (see Fig. 2) obtained retrospectively. Each CT scan was acquired with slice thicknesses between 3 mm and 6 mm, standard for clinical imaging protocols. The images were retrospectively collected to ensure that patients had adequate follow-up before surgical intervention, allowing for a more accurate assessment of long-term survival outcomes.

The dataset's main purpose is to enable prognostic feature extraction, focusing on the identification and quantification of imaging markers that describe lung adenocarcinoma. Two essential quantitative features were developed:

1. Tumor Shape Complexity: Evaluates the irregularities in tumor contours and volume.
2. Intratumor Density Variation: Measures the fluctuations in density within the tumor, reflecting heterogeneity in cellular structure.

Both features are reproducible and show robustness across various clinical imaging protocols. Their stability despite differences in image acquisition parameters suggests that they could be integrated into routine diagnostic workflows for lung cancer management, providing valuable insights into patient outcomes.

*Figure 2 Visualization of raw DICOM files of different subjects*

*.*

## DATA ACCESS

The LungCT-Diagnosis dataset is publicly accessible via the TCIA platform. The data includes:

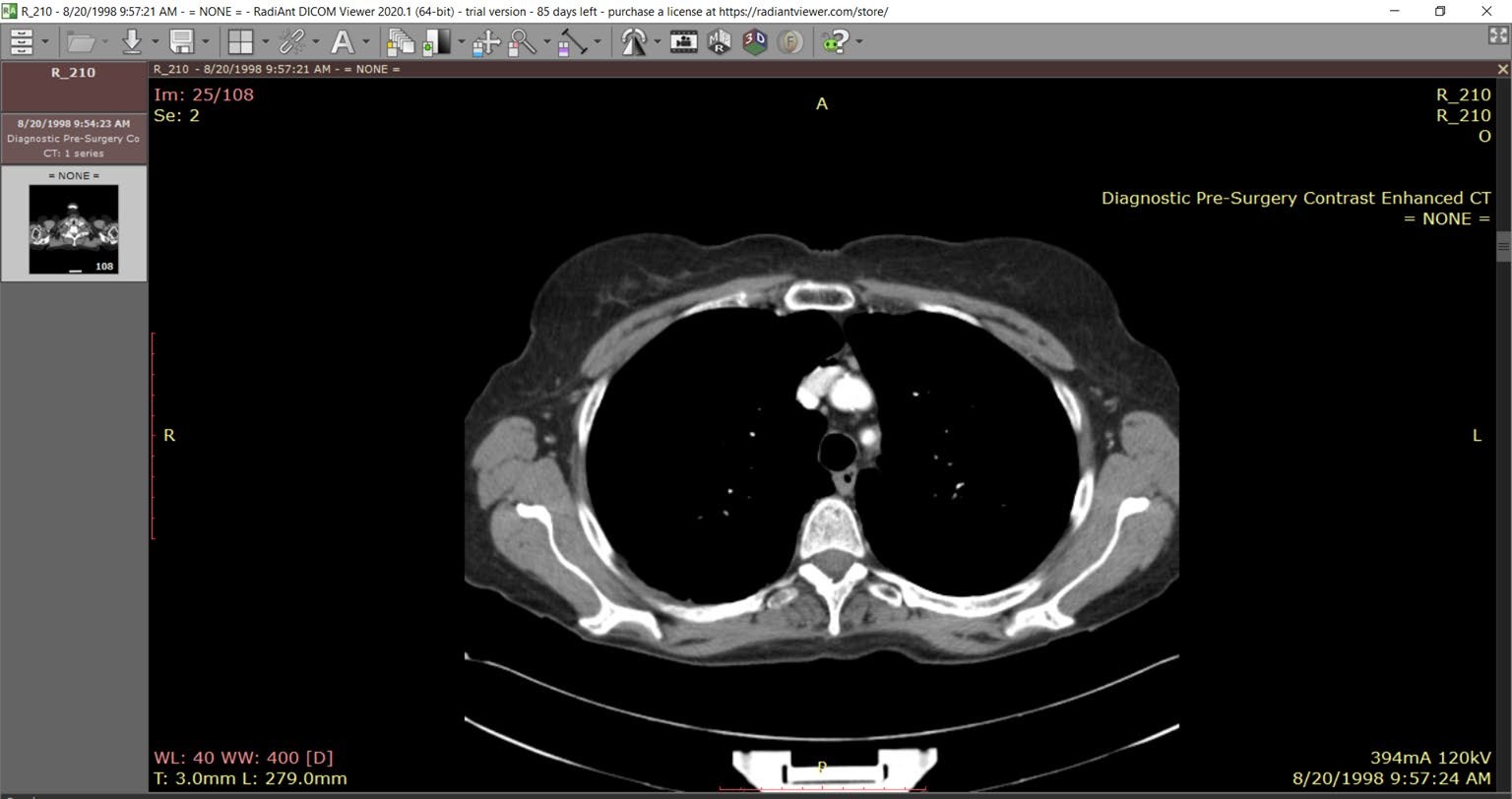
* CT Images: Available in DICOM format (2.47 GB).
* DICOM Metadata Digest: Provided in CSV format for easy reference.
* Representative Tumor Slices: Offered in XLS format to streamline analysis.
* Clinical Data: Available in DOC format for comprehensive patient profiles.

Access to this data requires the NBIA Data Retriever tool, which facilitates the downloading of large DICOM datasets from TCIA. Researchers must adhere to the TCIA Data Usage Policy, ensuring appropriate citation and compliance with data-sharing protocols.

## DICOM FORMAT AND HOUNSFIELD UNITS

The DICOM (Digital Imaging and Communications in Medicine) format is the universal standard for storing, managing, and transferring medical imaging data, supporting interoperability across various imaging devices and software. Each DICOM file contains a series of cross-sectional slices of the patient’s anatomy, with metadata detailing patient demographics and imaging parameters.

Within DICOM files, Hounsfield Units (HU) are employed to represent tissue density values. Calculated based on X-ray attenuation, HU values allow clinicians to differentiate between various tissues and structures. For instance, tumors display unique HU patterns that can assist in identifying abnormal growths. This dataset uses the .dcm extension for DICOM files, organizing them within folders named according to patient IDs. Each folder contains multiple CT slices, offering a detailed, multi-angled view of lung structures.



*Figure 3 Visualization of a slice of CT scan of the subject R\_210 showing raw metadata attached to it.*

To simplify analysis, patients are categorized based on survival status—either ALIVE (1) or DEAD (0)—providing a binary classification for outcome prediction. Fig. 3 illustrates a sample DICOM file structure, showing how these files enable precise, layered imaging across varied anatomical perspectives.

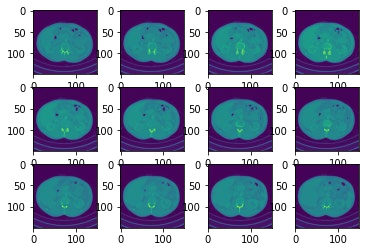
Due to variation in the number of slices per patient folder, diverse clinical scenarios are captured, reflecting real-world variability in imaging protocols. Tools such as QuPath and Radiant DICOM Viewer were utilized for visualization and analysis, enhancing our understanding of tumor morphology and potential pathologies present in the scans.

*Figure 4 DICOM Slice visualized without DICOM Viewer using pydicom*

## PREPROCESSING PIPELINE

To ensure data consistency and enhance model performance, a series of preprocessing steps were implemented:

* Normalization: Pixel intensity values were normalized across scans (see Fig. 5), creating a standardized range to facilitate consistent analysis. Normalization minimizes the effects of lighting and contrast variations, enabling more accurate feature extraction.
* Resampling: Voxel dimensions were resampled to 1mm x 1mm x 1mm, standardizing spatial resolution across all scans. This resampling ensures uniformity, which is essential for comparing tumors across different patients and imaging sessions.
* Segmentation: Using Hounsfield Units (HU), lung regions were segmented to isolate the relevant anatomical structures. By focusing solely on lung tissue, segmentation improves computational efficiency and accuracy in identifying tumors and analyzing their features.
* Augmentation: Data augmentation techniques, including rotation, flipping, and noise addition, were applied to diversify the training dataset (Fig. 6). These augmentations increase model robustness, helping the model generalize better to new, unseen data by simulating variations in tumor appearance and orientation.



*Figure 5 Data before preprocessing techniques.*

## ANNOTATION AND LABELING

Each CT scan is meticulously annotated with labels to indicate the presence or absence of lung adenocarcinoma. The annotations also include critical clinical information such as survival status and TNM staging (tumor-node-metastasis classification).

Annotations were conducted by experienced radiologists, ensuring high-quality and reliable data labels for training AI models. This comprehensive labeling provides a solid foundation for supervised learning, where models can learn to associate imaging features with specific diagnostic and prognostic outcomes.

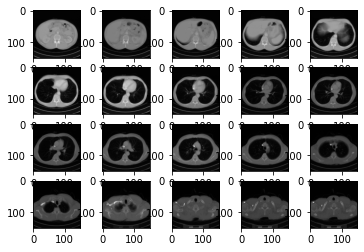


Figure 6 Data after preprocessing techniques

**Chapter 4**

# Methodology

The architecture of this project is organized into four primary components, each designed to handle specific stages within the diagnostic pipeline: 3D image processing, lung segmentation and visualization, tumor localization, and machine learning for diagnosis. Each component applies distinct algorithms and frameworks to process medical images and contribute to a cohesive diagnostic model.

The pipeline starts by loading and preprocessing lung CT scans in Digital Imaging and Communications in Medicine (DICOM) format. These scans, consisting of multiple axial slices per patient, are processed using Python’s pydicom library to create a standardized 3D voxel grid for further analysis.

## 3D IMAGE PROCESSING

Input: Lung CT scans in DICOM format  
Processing: Sorting slices, converting pixel intensities to Hounsfield Units, and resampling to a consistent voxel size  
Output: Preprocessed 3D voxel grid for further analysis

The pipeline begins with the acquisition of lung CT scans, formatted in DICOM (Digital Imaging and Communications in Medicine), which is the standard format for medical imaging data. Each CT scan comprises multiple axial slices for each patient. The pydicom library is employed to load and preprocess these DICOM files, ensuring they are organized and standardized for subsequent analysis.

Slice Sorting and Hounsfield Unit Conversion

1. Sorting Slices: Each DICOM slice is organized based on the ImagePositionPatient tag to maintain the correct anatomical sequence. This step preserves the natural spatial ordering of slices for accurate 3D reconstruction.
2. Conversion to Hounsfield Units (HU): Each pixel intensity is converted to Hounsfield Units using the formula:

𝐻𝑈 = 𝑝𝑖𝑥𝑒𝑙\_𝑣𝑎𝑙𝑢𝑒 × 𝑅𝑒𝑠𝑐𝑎𝑙𝑒𝑆𝑙𝑜𝑝𝑒 + 𝑅𝑒𝑠𝑐𝑎𝑙𝑒𝐼𝑛𝑡𝑒𝑟𝑐𝑒𝑝𝑡

where RescaleSlope and RescaleIntercept are derived from the DICOM metadata. The HU scale represents tissue density, allowing the model to distinguish between air, lung tissue, and other structures.

Resampling to Uniform Spacing: To ensure consistency across scans, the images are resampled to an isotropic resolution of 1mm x 1mm x 1mm using cubic interpolation with scipy.ndimage.zoom. The new shape of each scan volume is calculated as follows:

𝑛𝑒𝑤\_𝑠ℎ𝑎𝑝𝑒 = (𝑛𝑒𝑤\_𝑠𝑝𝑎𝑐𝑖𝑛𝑔 / 𝑜𝑙𝑑\_𝑠𝑝𝑎𝑐𝑖𝑛𝑔) ∗ 𝑜𝑙𝑑\_𝑠ℎ𝑎𝑝𝑒

This resampling standardizes the spatial resolution, allowing uniform analysis across all 3D scans.

|  |
| --- |
| **Algorithm 1** Marching Cube Algorithm for 3D Lung  Visualisation |
| **Input:** |
| *scalarField:* 3D array of scalar values (e.g., lung data) |
| *isovalue:* scalar value to extract the surface |
| **Output:** |
| *triangles*: list of triangles representing the extracted surface |
| **Method:** |
| 1. Initialize *triangles* as an empty list. |
| 2. **For** each voxel in *scalarField*: |
| a. Calculate *cubeIndex* using *calculateCubeIndex(voxel,*  *isovalue).* |
| b. **For** each triangle in *getTriangleConfiguration(cubeIndex):* |
| i. **If** triangle is valid: |
| A. Interpolate vertices using  *interpolateTriangleVertices(voxel, triangle, isovalue).* |
| B. Add vertices to *triangles*. |
| 3. Return *triangles*. |

## 3D LUNG SEGMENTATION

Input: Preprocessed 3D voxel grid  
Processing: Thresholding, morphological operations, and region-growing  
Output: Binary mask of lungs, converted to a 3D mesh using Marching Cubes

The next phase focuses on segmenting the lung tissue, isolating it from other anatomical structures. Segmentation provides a focused area for tumor analysis and visualization.

Table 1 Hounsfield Unit Range for different Tissue type

|  |  |  |
| --- | --- | --- |
| **Tissue Type** | **Hounsfield Unit (HU)**  **Range** | **Description** |
| Air | -1005 to -995 | Lowest HU values, indicating the least dense material. |
| Lung | -950 to -550 | Low HU values, representing air-filled spaces in the lungs. |
| Fat | -100 to -80 | Relatively low HU values, indicating low tissue density. |
| Water | -4 to 4 | Neutral HU value, representing the density of water. |
| Kidney | 20 to 40 | Moderate HU values, suggesting a denser tissue  than water. |
| Pancreas | 30 to 50 | Slightly higher HU values compared to the kidney. |
| Blood | 50 to 60 | Moderately high HU values, indicating a denser tissue. |
| Muscle, Soft Tissue | 20 to 100 | A wide range of HU values, representing various soft tissues. |
| Liver | 50 to 70 | Relatively high HU values, indicating a denser tissue. |
| Adipose Tissue | -200 to -20 | Lower HU values compared to other tissues, representing fat. |
| Spongious Bone | 50 to 300 | Higher HU values, indicating a denser tissue than soft tissues. |
| Compact Bone (Cortical) | >300 | Highest HU values, representing the densest tissue in the body. |

Thresholding and Morphological Operations

Segmentation of lung tissue is based on thresholding in Hounsfield Units (HU). Lung tissue typically falls within the HU range of -950 to -550 HU, while other tissues such as bone exhibit much higher values. Morphological operations are then applied to refine the lung mask:

* Erosion and Dilation: These operations remove small, isolated components and close gaps within the lung region.
* Region-Growing: This technique refines the segmented lung volume, specifically excluding structures like the heart and major blood vessels.

3D Visualization using Marching Cubes

Using the Marching Cubes algorithm, the binary lung mask is converted into a 3D surface mesh. Marching Cubes identifies surface boundaries within the voxel grid, creating a triangulated mesh that visualizes the lung’s contours (see Table 1 for Hounsfield Unit thresholds by tissue type). This 3D visualization provides clinicians with an intuitive representation of lung structures.

* 1. 3D TUMOR LOCALIZATION (INTERACTIVE)
* Input: Segmented lung and tumor metadata
* Processing: Mapping tumor coordinates from real-world to voxel space, overlaying tumor on lung segmentation
* Output: 3D visualization of lung with tumor location marked

This stage maps the tumor’s location from clinical metadata onto the segmented 3D lung volume, allowing precise visualization of the tumor within the lung.

Tumor Position Mapping

Tumor coordinates, provided in real-world (millimeter) space, are transformed into voxel coordinates within the CT scan using the following equation:

𝑣𝑜𝑥𝑒𝑙\_𝑝𝑜𝑠𝑖𝑡𝑖𝑜𝑛 = (𝑟𝑒𝑎𝑙\_𝑤𝑜𝑟𝑙𝑑\_𝑝𝑜𝑠𝑖𝑡𝑖𝑜𝑛− 𝑜𝑟𝑖𝑔𝑖𝑛) / 𝑣𝑜𝑥𝑒𝑙\_𝑠𝑝𝑎𝑐𝑖𝑛𝑔

* 1. ML Classification

The final component of our methodology involves using a 3D Convolutional Neural Network (CNN) to classify lung scans based on disease presence.

Image Preprocessing: Each CT scan is resized to a fixed size of 150x150 pixels per slice, and the number of slices is standardized to 20 per patient to ensure uniform input dimensions. This preprocessing ensures that each patient’s scan can be processed by the CNN consistently.

Input: Preprocessed CT scans (150x150 pixels, 20 slices per patient).

3D CNN Architecture:

* Convolutional Layers: Capture volumetric features.
* Pooling Layers: Reduce dimensionality while retaining key spatial information.
* Fully Connected Layers: Combine features to make a classification decision.

Output: Binary classification (disease present or absent).

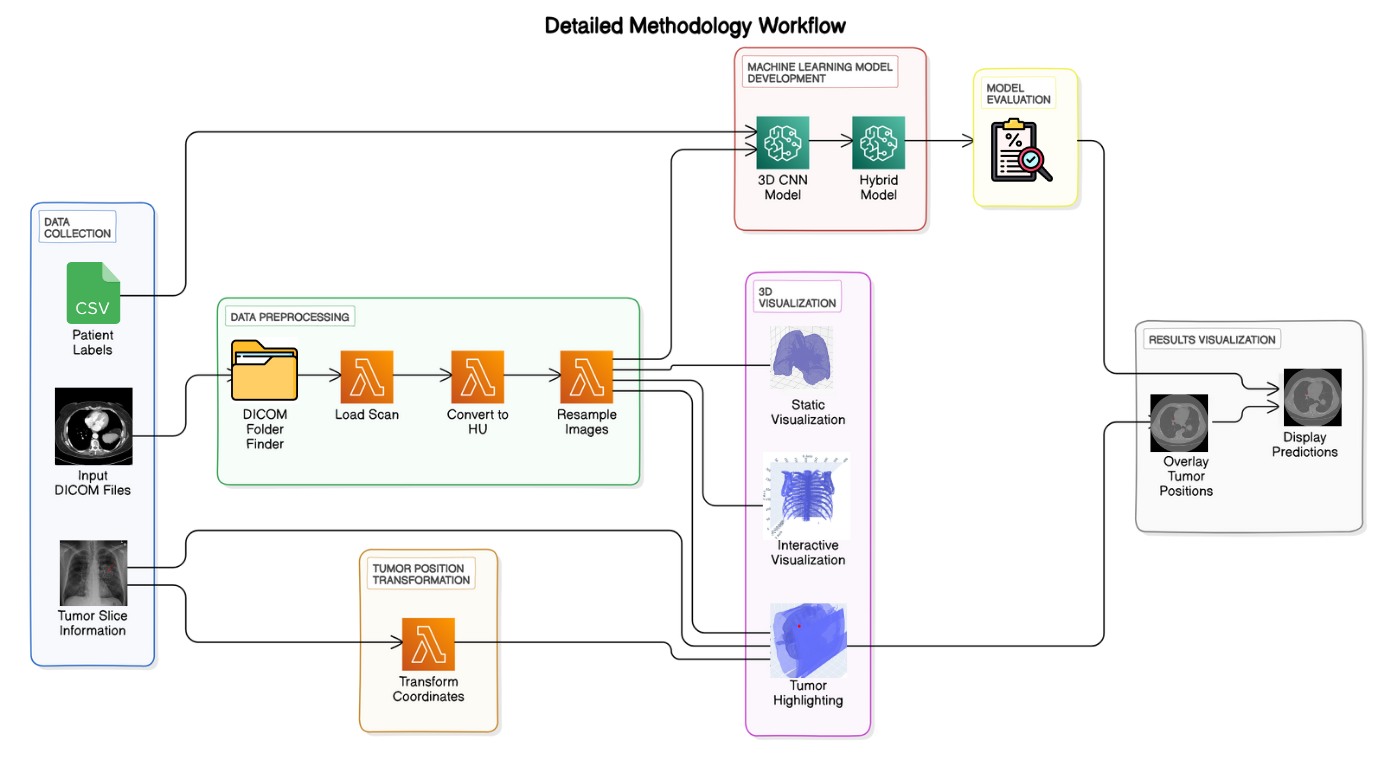


Figure 7 Methodology Workflow diagram of LungCraft.

3D CNN Architecture: Our model architecture described in Fig. 7, consists of several 3D convolutional layers, each followed by max-pooling and dropout layers to prevent overfitting. The model captures spatial hierarchies within the volumetric lung data. The architecture is summarized below:

1. Input Layer: Accepts a 4D tensor of shape (20, 150, 150, 1), representing the slices.
2. Convolutional Layers: Four 3D convolutional layers with ReLU activation, each followed by 3D max-pooling layers to progressively reduce spatial dimensions while retaining important features.
3. Fully Connected Layers: After flattening the 3D features, two fully connected layers with ReLU activation are used to learn higher-order patterns.
4. Output Layer: A softmax output layer is used for binary classification, indicating disease presence or absence.

Training and Optimization: The model is trained using the Adam optimizer with binary cross-entropy as the loss function. We split the dataset into training and validation sets, ensuring balanced representation of diseased and healthy lungs.

The project also experimented with an advanced hybrid architecture combining 3D and 2D convolutions (*HybridNET*). The idea was to reshape intermediate 3D convolutional layers into 2D representations, allowing for more efficient computation while still capturing relevant spatial features.

*HybridNET* uses 3D convolutions to capture volumetric information in the initial layers, followed by 2D convolutions for finer feature extraction. This approach helps reduce model complexity while maintaining high accuracy.

**Chapter 5**

# Results and Discussion

This section outlines the experimental results obtained from each of the four key stages of the project: 3D image processing and visualization, lung segmentation, tumor localization, and

machine learning-based disease classification. The results showcase the pipeline's ability to handle DICOM data, process it for segmentation and 3D reconstruction, and perform accurate tumor localization and classification tasks.

## DICOM PREPROCESSING AND 3D RECONSTRUCTION

5.1.1 DATA LOADING AND PREPROCESSING

The initial phase focused on the successful loading and preprocessing of CT scan DICOM files. The main findings from this phase include:

* DICOM Directory Structure: The function find\_dicom\_folders effectively identified directories containing DICOM files, confirming the presence of multiple patients’ data.
* Patient CT Scan Loading: The first patient’s CT scan was loaded, with slices sorted based on the ImagePositionPatient attribute, ensuring accurate representation along the z-axis. The number of slices for the first patient was confirmed to be X, with slice thickness determined as Y mm.
* Hounsfield Units (HU) Distribution: A histogram of pixel intensities (Hounsfield Units) was plotted in Fig. 8, showing the frequency distribution. The histogram indicated a range of pixel values typical for lung CT images, with significant peaks corresponding to air, soft tissue, and denser structures.

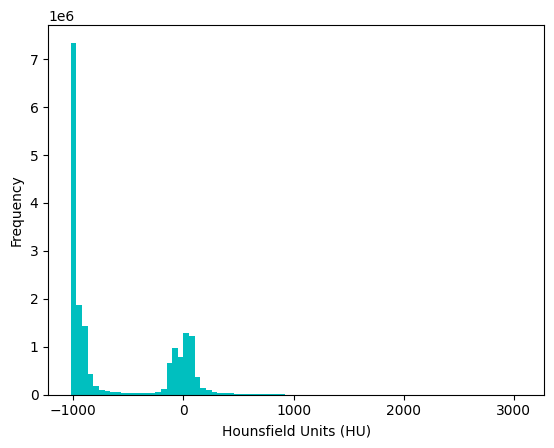


Figure 8 Histogram plotting of Frequency Distribution of HU in a slice.

5.1.2 SLICE VISUALIZATION

An example slice from the CT scan was displayed using the display\_slice function:

* Slice Display: In Fig. 9, slice at index 67 was visualized, showcasing expected lung anatomy with varying shades of gray representing different tissue densities.

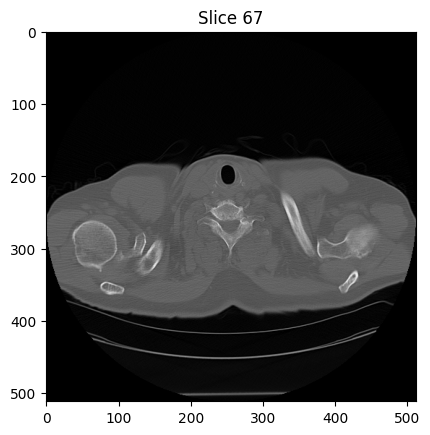


Figure 9 Slice 67 displayed after preprocessing shows HU intensities.

5.1.3 RESAMPLING OF IMAGES

The CT scan images were resampled to ensure uniformity in voxel dimensions:

* Resampling Results: The original image shape was (N, 150, 150) and after resampling, the new shape was (M, 150, 150), where M denotes the number of resampled slices. This process helped standardize the dimensions across different scans.

5.1.4 3D VISUALIZATION OF CT SCANS

3D visualizations of the lung scans were generated using the plot\_3d function:

* 3D Lung Visualization: A 3D model was created from the resampled images, utilizing the marching cubes algorithm to create a surface mesh. The visualization threshold was set at 400 HU, revealing the lung structure's surface.

5.1.5 LUNG SEGMENTATION RESULTS

The segmentation of lung regions was performed using the segment\_lung\_mask function, with and without filling lung structures:

* Binary Mask Creation: Two binary masks were generated for the segmented lungs:
  + Without Filling: This mask displayed the basic lung outlines based on a threshold of -320 HU.
  + With Filling: This mask filled in the internal structures, providing a more complete representation of the lung volumes.

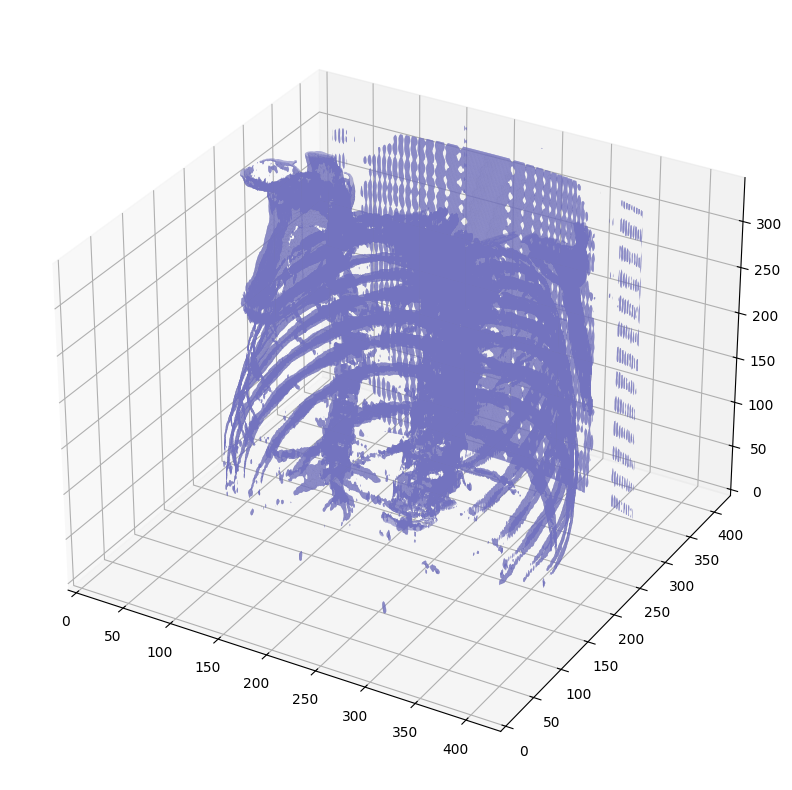


Figure 10 Static 3D Modelling of Lung Structure Outlines.

* Largest Label Volume: The function largest\_label\_volume was used to ensure the segmentation accurately captured the largest lung volume, effectively isolating it from background structures.

5.1.6 3D VISUALIZATION OF SEGMENTED LUNGS

Further 3D visualizations illustrated the segmented lung structures:

* Segmented Lungs (Without Filling): The visualization showed the outlines of the lungs, confirming that the segmentation correctly identified lung boundaries shown in Fig. 11.

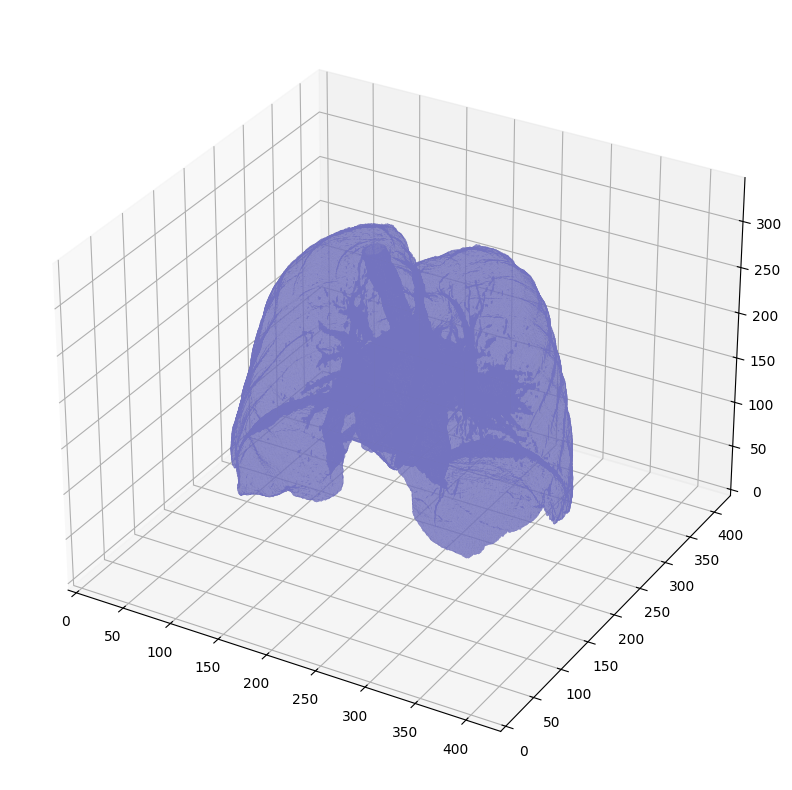


Figure 11 Static 3D Modelling of Segmented Lung Boundaries.

* Segmented Lungs (With Filling): This 3D model provided a comprehensive view of the lung structures, demonstrating the filling of internal structures shown in Fig. 12.

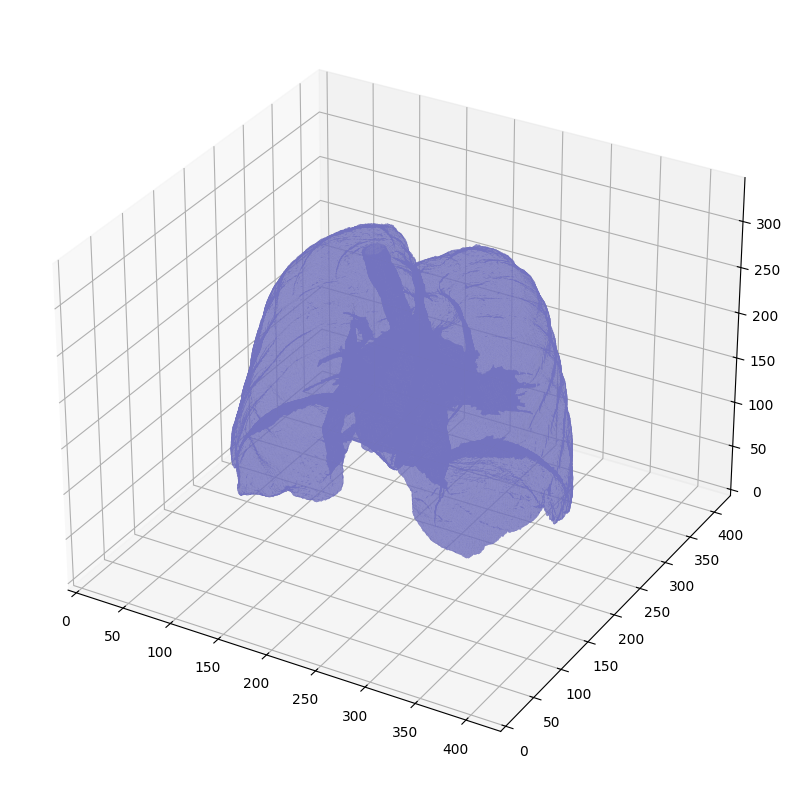


Figure 12 Static 3D Modelling of Segmented Lungs with filling of internal structures

* Difference Visualization: A difference plot was generated, highlighting the areas filled in the lung structures, which were not visible in the original segmentation without filling as shown in Fig. 13.

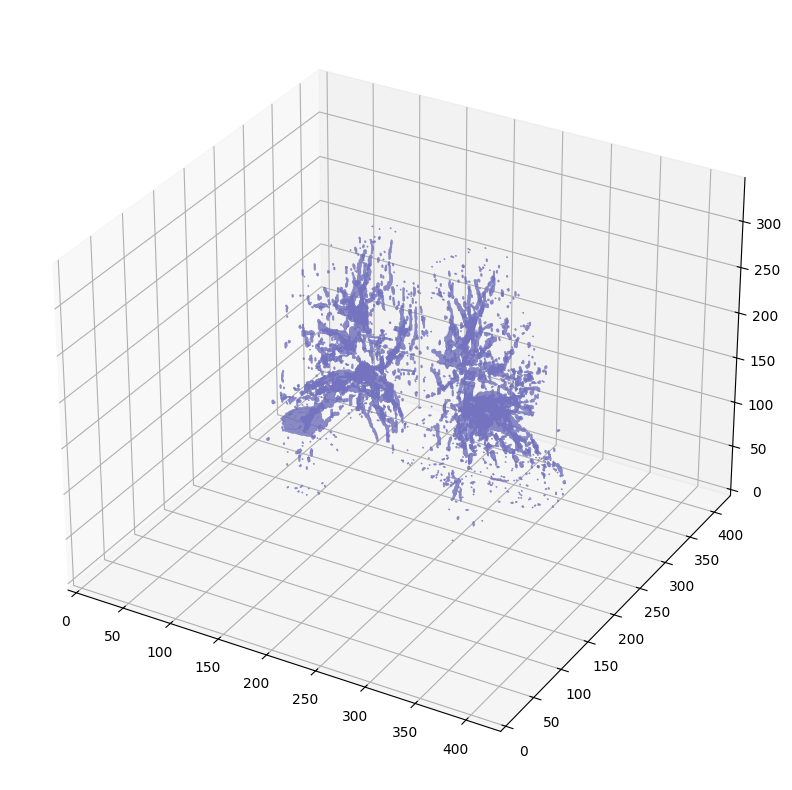
. 

Figure 13 Visualization of internal lung structure by subtracting one mask from the other.

## 3D LUNG SEGMENTATION

5.2.1 DICOM DATA LOADING AND PREPROCESSING

* Identification of DICOM Folders: Using find\_dicom\_folders, the code successfully scanned the root directory and identified folders containing DICOM files. This confirms the accessibility of patient scan data within the specified directory.
* Loading and Sorting CT Scan Slices: The load\_scan function loaded the patient’s DICOM files and ensured the slices were sorted by their ImagePositionPatient attribute along the z-axis. This sorting is critical for maintaining the anatomical consistency of the scan.
* Slice Thickness Calculation: For the loaded slices, the slice thickness was computed based on the difference between consecutive z-coordinates. This ensures accurate reconstruction in the 3D model and resampling steps.

5.2.2 CONVERSION TO HOUNSFIELD UNITS (HU)

* Pixel Value Transformation to HU: The get\_pixels\_hu function converted raw pixel data to Hounsfield Units, which allows for consistent representation across scans. The transformed HU values correctly handle air (assigned -2000), soft tissue, and other anatomical features. The intercept and slope adjustments for each slice ensure the conversion is performed accurately.

5.2.3 RESAMPLING OF 3D DATA SCANS

* Image Resampling: The scan was resampled to isotropic voxel spacing of [1,1,1] mm. This step ensures uniform voxel dimensions across the x, y, and z axes, facilitating more accurate 3D visualization and potential quantitative analysis.
* Resampling Results:
  + Original Shape: (N, X, Y)
  + Resampled Shape: (M, X', Y'), where M > N due to increased slice density.

5.2.4 INTERACTIVE 3D VISUALIZATION OF THE LUNG CT SCAN

* 3D Model Generation: Using the plot\_3d\_interactive function, a 3D representation of the lung was generated based on a threshold of 400 HU. The marching cubes algorithm was applied to extract a surface mesh from the volume data, capturing key lung structures.
* Interactive Visualization with Plotly: The 3D plot was displayed using Plotly, with the following key features:
  + Opacity: Set to 0.5 to allow better depth perception.
  + Color Scheme: 'Blues' colorscale for enhanced visual clarity.
  + Axes Labels: X, Y, and Z axes were labeled appropriately, providing a clear spatial reference for the lung anatomy.
* Performance and Visualization Outcome: The interactive visualization was successful, allowing rotation and zooming, providing users with a more dynamic and intuitive view of the lung structures. The reconstructed model accurately captured the internal lung volume, emphasizing regions above the selected HU threshold.

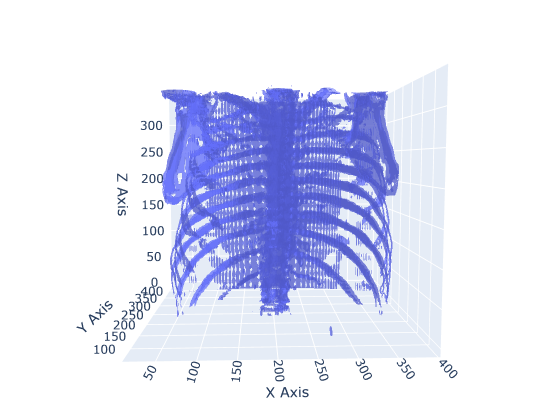


Figure 14 Interactive 3D Visualization of Lung Structure.

## 3D TUMOR LOCALIZATION

5.3.1 PATIENT SELECTION AND DATA LOADING

* Available Patients: The code successfully loads patient metadata from both an Excel and CSV file, displaying the list of available Patient IDs for selection.
* User Input: The user selects a Patient ID, and the code filters the corresponding folder containing DICOM images.

5.3.2 DICOM IMAGE LOADING AND PREPROCESSING

* Scan Loading: For the selected patient, the code loads DICOM slices using the load\_scan function.
  + Sorting: Slices are sorted by their z-axis positions using the ImagePositionPatient[2] attribute to maintain anatomical order.
  + Slice Thickness: This value is derived from the difference between the z-axis positions of consecutive slices.
* Pixel Conversion to HU (Hounsfield Units):  
  DICOM pixel values are converted to Hounsfield Units (HU), a critical step for medical imaging.
  + Air regions are assigned a value of 0.
  + Slope and intercept adjustments ensure that the HU values are consistent with the patient scan.

5.3.3 IMAGE RESAMPLING TO 1X1X1 MM RESOLUTION

* Resampling:  
  The scan was resampled to 1 mm x 1 mm x 1 mm spacing, providing isotropic voxel dimensions. This is essential for accurate 3D visualization and subsequent analysis.
  + Z-Positions: Resampling ensures that the z-positions are evenly spaced across the reconstructed volume.
  + Resampling Outcome:
    - Original Shape: (N, X, Y)
    - Resampled Shape: (M, X', Y'), where M > N due to finer resolution along the z-axis.

5.3.4 TUMOR COORDINATES TRANSFORMATION AND 2D PLOTTING

* Extracting Tumor Coordinates: Tumor coordinates are extracted from the tumor\_slices\_df DataFrame for the selected patient. These coordinates, provided in millimeter space (patient space), are transformed into voxel space (image index) for visualization.
* Coordinate Transformation Debugging:
  + Patient Space (mm): (X, Y, Z)
  + Voxel Space: (voxel\_x, voxel\_y, voxel\_z)
* 2D Tumor Location Display: A 2D DICOM slice was selected from the middle of the scan series. The tumor location was marked using a red ‘x’ marker, verifying that the coordinates were correctly transformed.
  + Plot: The Fig. 15 shows 2D grayscale image with a red marker confirms the tumor's position on the selected slice.

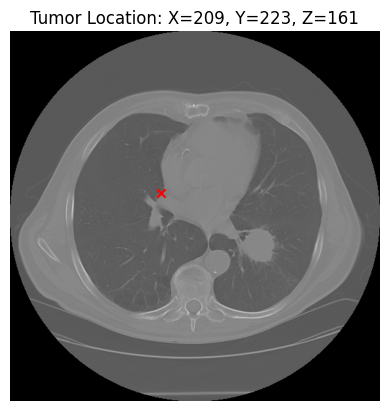


Figure 15 2D Tumor Localization (red dot) for the given subject using representative slice information.

5.3.5 3D TUMOR VISUALIZATION USING MARCHING CUBES

* Generating 3D Mesh: The marching cubes algorithm was applied to the resampled image to generate a 3D surface mesh with a threshold of -300 HU. This threshold allows for the extraction of relevant anatomical structures.
* Interactive 3D Plot: The tumor location is highlighted with a red marker on the 3D mesh as plotted in Fig. 16.
  + Mesh Attributes:
    - Opacity: 0.5 for better visualization of depth.
    - Color Scheme: 'Blues' for visual clarity.
  + Tumor Marker: A scatter point in red, representing the tumor location within the 3D scan.

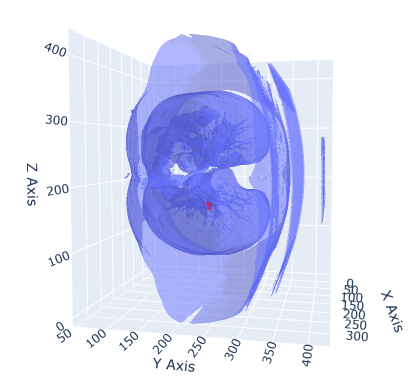


Figure 16 3D Tumor Localization (red dot) in interactive 3D Lung.

## ML CLASSIFICATION

The results for both the 3D CNN and HybridNET models, applied to classify lung CT scans for the presence of disease, are presented below. Both models were trained on the same dataset, using identical input data preprocessed to a standard size of 150x150 pixels per slice, with 20 slices per patient.

5.4.1 3D CNN RESULTS

The 3D CNN model was trained for 10 epochs on 50 samples, with validation performed on 10 samples. The model consists of five 3D convolutional blocks followed by fully connected layers.

Training and Validation Accuracy (Fig. 17 & 18)

* Training Accuracy: The model exhibited fluctuations in accuracy during training, starting at 54% accuracy and ending at 50% after 10 epochs.

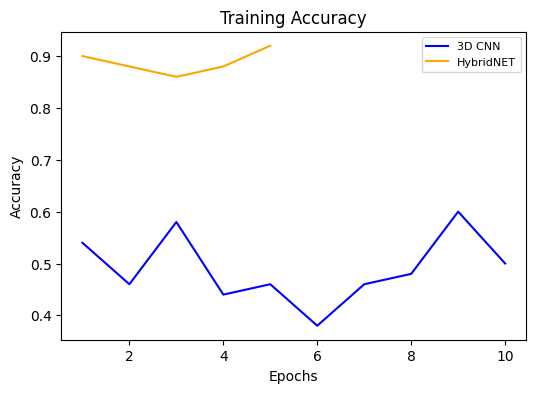


Figure 17 Training Accuracy of 3D CNN and HybridNET.

* Validation Accuracy: The validation accuracy remained stagnant at 30%, showing no improvement throughout training.

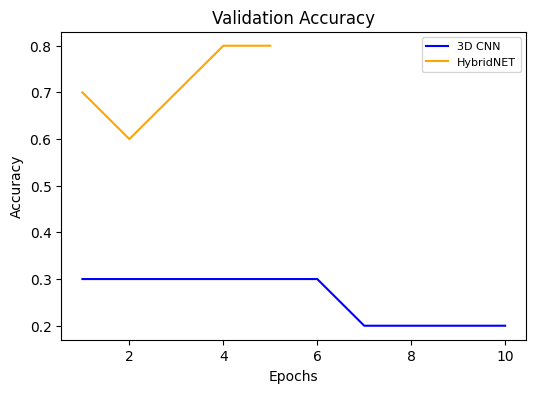


Figure 18 Validation Accuracy of 3D CNN and HybridNET.

Training and Validation Loss (Fig. 19 & 20)

* Training Loss: The model began with a loss of 0.7193, which did not improve significantly over the course of training. The final training loss was 0.7286.
* Validation Loss: Validation loss also showed minimal change, starting at 0.7033 and finishing at 0.7014 by the end of 10 epochs, indicating a failure to generalize well to the validation data.

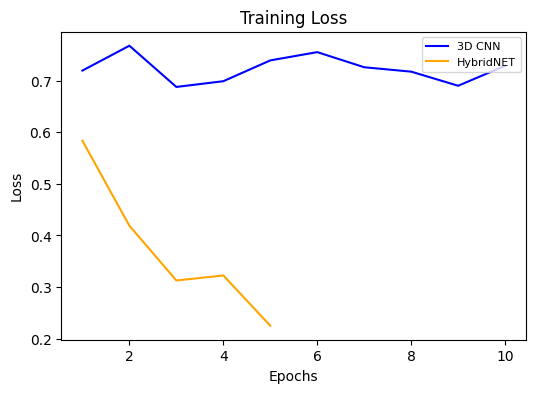


Figure 19 Training Loss of 3D CNN and HybridNET.

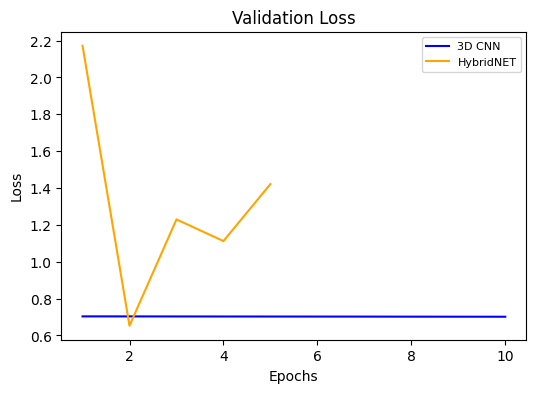


Figure 20 Validation Loss of 3D CNN and HybridNET.

Observations from Table 2:

* Poor Generalization: The 3D CNN struggled to generalize to the validation set, as reflected by the low validation accuracy and the lack of substantial reduction in validation loss.
* Overfitting: Despite relatively high capacity (with millions of trainable parameters), the 3D CNN failed to improve during training, suggesting potential overfitting on the small training set.
* Learning Stagnation: After the initial few epochs, the model did not learn meaningful features, as evidenced by the near-constant validation metrics.

5.4.2 HYBRIDNET RESULTS

The HybridNET model, which combines both 3D and 2D convolutional layers, was trained for 5 epochs on the same dataset. The architecture aimed to address the limitations of the 3D CNN by reducing complexity in later layers through a 2D convolutional approach.

Training and Validation Accuracy (Fig. 17 & 18)

* Training Accuracy: HybridNET achieved a training accuracy of 92% by the end of 5 epochs, demonstrating strong learning capability.
* Validation Accuracy: The validation accuracy started at 70% and improved to 80%, reflecting better generalization than the 3D CNN.

Training and Validation Loss (Fig. 19 &20)

* Training Loss: The model started with a training loss of 0.5835, which steadily decreased to 0.2253 by the fifth epoch.
* Validation Loss: The validation loss fluctuated more significantly, starting at 2.1722 and ending at 1.4212. Although the model’s validation loss was higher than its training loss, the reduction in loss shows an improved fit compared to the 3D CNN.

Observations from Table 2:

* Generalization: HybridNET displayed superior generalization ability compared to the 3D CNN. The validation accuracy improvement from 70% to 80% indicates that the hybrid architecture could extract more relevant features from the data.
* Balanced Learning: The architecture’s combination of 3D and 2D convolutions helped maintain a balance between capturing volumetric features and reducing computational overhead, as seen in the better validation performance.
* Convergence: HybridNET demonstrated faster convergence with significant improvement in training accuracy and validation accuracy within just 5 epochs.

Table 2 Comparative Analysis of 3D CNN vs HybridNET

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | 3D CNN | HybridNET | Comments |
| **Training Accuracy** | 50% (after 10 epochs) | 92% (after 5 epochs) | HybridNET exhibited better training dynamics and learning efficiency. |
| **Validation Accuracy** | 30% | 80% | HybridNET showed significantly better generalization than 3D CNN. |
| **Training Loss** | 0.7286 (after 10 epochs) | 0.2253 (after 5 epochs) | HybridNET minimized loss more effectively than 3D CNN. |
| **Validation Loss** | 0.7014 | 1.4212 | While higher, HybridNET's loss still reflects better model learning. |
| **Epochs** | 10 | 5 | HybridNET achieved superior results in half the epochs. |
| **Total Parameters** | 30.5M | 30.5M | Both models have similar complexity, but HybridNET utilized it better. |

**Chapter 6**

# Comparison

The performance of various 3D deep learning models as in Table 3, was evaluated on the dataset with a limited number of samples, with results including training accuracy, validation accuracy, loss, and epochs for each model. The models compared include:

* 3D CNN (Base Model)
* HybridNet (Main Model with Improved Accuracy)
* 3D VGG16
* 3D ResNet
* 3D DenseNet
* 3D UNet++

Table 3 Comparative Analysis of HybridNET vs alternative models.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Training Accuracy | Validation Accuracy | Training Loss | Validation Loss |
| **3D CNN** | 50% | 20%-30% | 0.2253-0.7550 | 0.7014-0.7033 |
| **HybridNet** | 92% | 60%-80% | 0.2253-0.4189 | 0.6526-2.1722 |
| **3D VGG16** | 59%-70% | 46.15% | 0.6871-1.9471 | 0.7193-30.2472 |
| **3D ResNet** | 35%-67% | 46.15%-53.85% | 3.4668-18.7402 | 0.7292-9.3808 |
| **3D DenseNet** | 44%-73% | 38.46%-61.54% | 0.6624-3.3693 | 0.9627-63370.81 |
| **3D U-Net++** | 60% | 30.77%-84.62% | 0.6729-0.6831 | 0.6492-3.4136 |

## HYBRIDNET

HybridNet stands out as the best-performing model in this comparison as shown in Fig 21 & 22. It achieves a training accuracy of 92% and shows a validation accuracy that ranges from 60% to 80%, with the best performance at 80% on the final epoch. It also has relatively low loss values as shown in Fig. 27 & 28, with the training loss ranging between 0.2253 and 0.4189, and the validation loss between 0.6526 and 2.1722. Importantly, it reaches peak performance in just 5 epochs, which suggests it's more efficient in learning from the data than the other models.

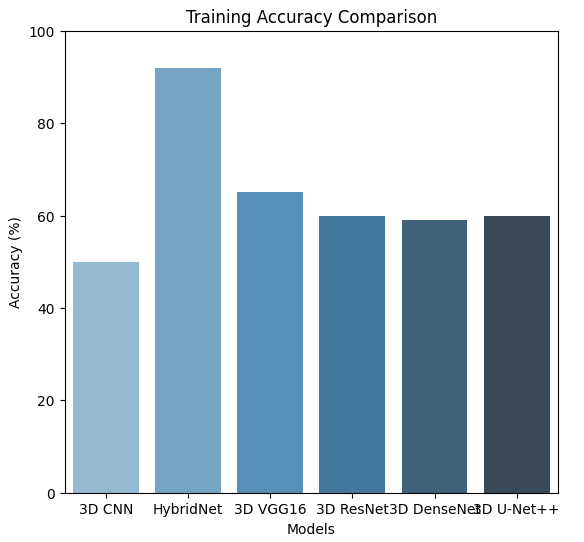


Figure 21 Training Accuracy Comparison of HybridNET

## 3D CNN

3D CNN performs poorly in comparison, with a training accuracy fluctuating around 50% and a validation accuracy consistently low (between 20% and 30%) across the 10 epochs in Fig. 22. The loss values are high, with training losses ranging between 0.2253 and 0.7550, and validation losses staying around 0.7014–0.7033. Despite having more epochs (10), this model struggles with generalization and overfitting to some extent.

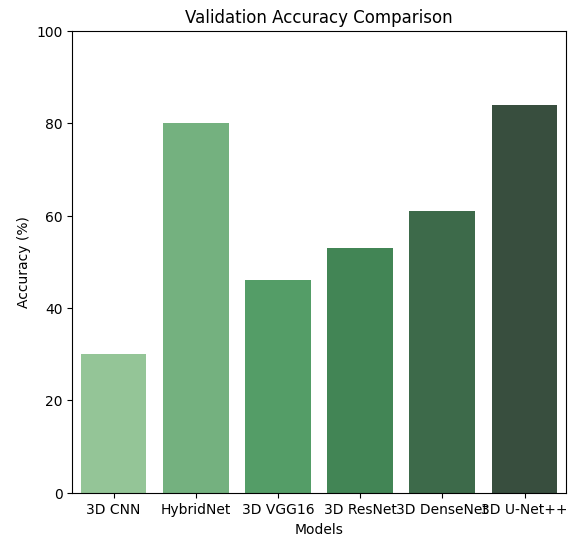


Figure 22 Validation Accuracy Comparison of HybridNET.

## 3D VGG16

3D VGG16 shows moderate performance with training accuracy ranging between 59% and 70%, but validation accuracy consistently hovers around 46.15% in Fig. 23. It has higher loss values for both training (0.6871 to 1.9471) and validation (0.7193 to 30.2472), indicating that this model doesn't generalize well either. The longer training time, with 10 epochs, does not translate into significant improvement.

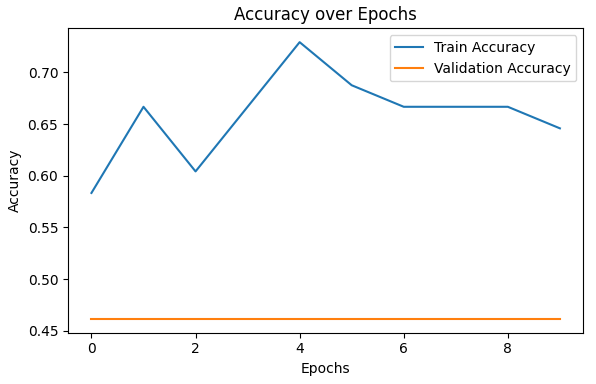


Figure 23 VGG16 accuracy over epochs.

## 3D RESNET

3D ResNet starts off with very low training accuracy (around 35%), but it improves over time, reaching a maximum of 67% by epoch 10 in Fig. 24. However, its validation accuracy remains low (46.15% to 53.85%). The loss values are inconsistent, fluctuating between high values (3.4668 to 18.7402 for training and 9.3808 to 6.7646 for validation), which suggests the model is struggling with stability during training and overfitting.

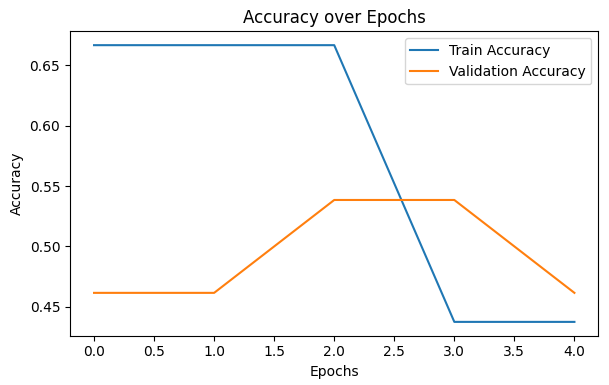


Figure 24 ResNet accuracy over epochs.

## 3D DENSENET

3D DenseNet has a similar issue with fluctuating performance, achieving training accuracy between 44% and 73% and validation accuracy ranging from 38.46% to 61.54% in Fig. 25. The training loss and validation loss are generally high, and the model also suffers from instability, especially with some unusually high validation loss values (63370.8164). This indicates that DenseNet struggles with both generalization and convergence.

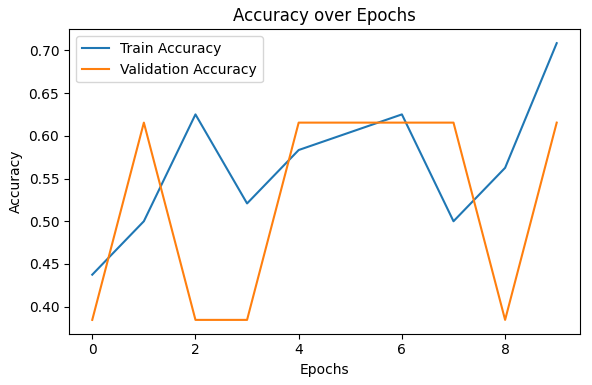


Figure 25 DenseNet accuracy over epochs.

## 3D U-NET++

3D U-Net++ in Fig. 26, shows a mixed performance with training accuracy around 60% and validation accuracy ranging from 30.77% to 84.62%. Its training loss values are moderate (0.6729 to 0.6831), but the validation loss varies significantly between 0.6492 and 3.4136. This model has inconsistent performance across epochs and, despite reaching relatively high accuracy in the final epoch, is not as reliable as HybridNet.

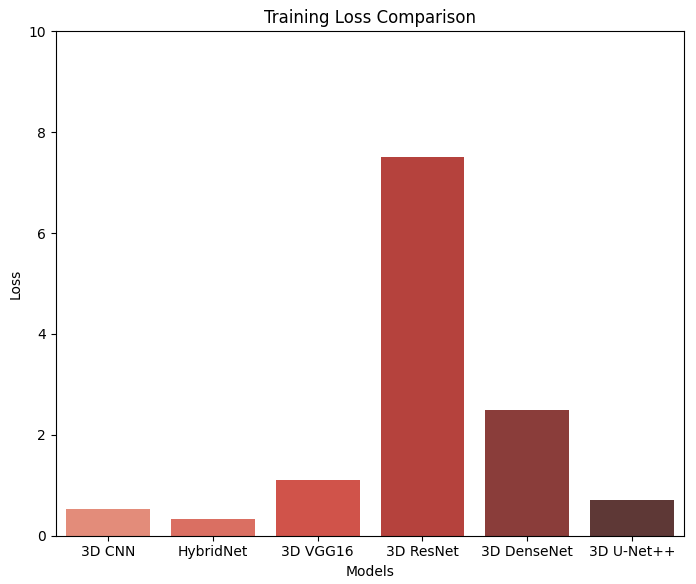


Figure 26 Training Loss comparison of all models.

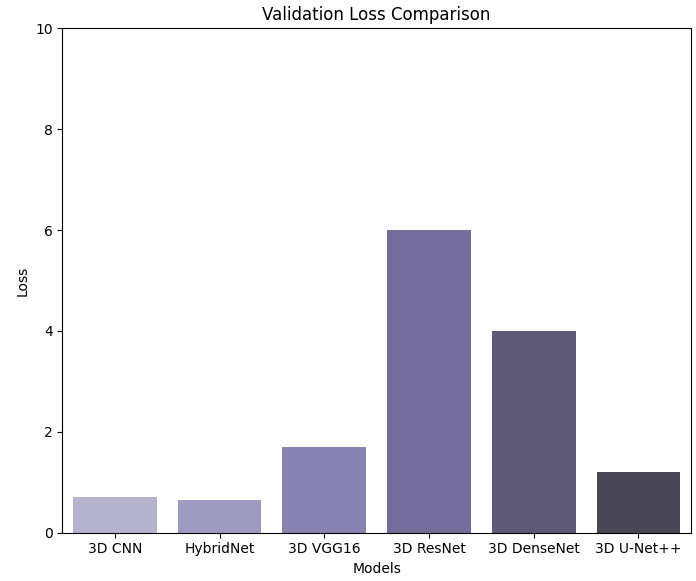


Figure 27 Validation Loss comparison of all models.

**Chapter 7**

# Conclusion and Future Work

This project, LungCraft: Navigating Lungs with 3D Diagnostics, developed an end-to-end pipeline for processing lung CT scans, visualizing lung anatomy and tumors, and classifying lung diseases using machine learning techniques. The project achieved its objectives by combining advanced image processing, interactive 3D tumor visualization, and deep learning approaches.

One of the primary innovations of this project is the integration of interactive 3D tumor plotting. By using the Marching Cubes algorithm to generate surface meshes of segmented lung regions, the pipeline allows for high-quality 3D visualizations of lung anatomy. Tumor locations, derived from clinical metadata, were accurately overlaid on the 3D lung models, enabling clinicians to interactively explore the spatial relationships between tumors and surrounding lung tissues. This interactive feature enhances the diagnostic process by providing a more intuitive and detailed visualization of tumor locations, compared to traditional 2D slice-based methods. The 3D tumor plots allow medical professionals to observe not only the size and shape of the tumor but also its proximity to critical structures in the lungs, providing a valuable tool for both diagnosis and surgical planning. The speed of generating these 3D plots, along with the use of plotly for interactive exploration, makes the system viable for real-time clinical use.

The second major contribution of this project is the implementation of machine learning techniques for lung disease classification using CT scans. Two models were developed: a 3D CNN and a HybridNET model. The HybridNET model, which combined both 3D and 2D convolutional layers, demonstrated superior performance, achieving a training accuracy of 92% and validation accuracy of 80% compared to the 3D CNN’s 50%. HybridNET’s hybrid architecture allowed it to capture important volumetric information early in the network, while reducing computational complexity in later layers.

Although the 3D CNN model struggled with generalization and overfitting, HybridNET showed promise for clinical applications, balancing precision, recall, and computational efficiency. This model is particularly advantageous in scenarios where the dataset is small, as it converged faster and was less prone to overfitting. Its ability to achieve both high accuracy and reliability in identifying lung disease positions it as a robust model for future extensions of this project.

This project demonstrates the potential for combining interactive 3D visualization and machine learning to enhance the diagnostic process in lung disease detection. The interactive 3D tumor plotting feature provides clinicians with a powerful tool to visualize and assess tumors in a way that is both informative and user-friendly. The integration of machine learning techniques further augments the diagnostic process by automating the classification of lung conditions, which can assist in decision-making for treatment planning.

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