Supervised 3D Volume Reconstruction from Sparse 2D CT Slices using conv3D Autoencoder

Submitted by

Anika Tabassum Adrita
221-35-882
Department of Software Engineering
Daffodil International University

Supervised by
Fatema Binte Rafiq Lecturer (Senior Scale)
Department of Software Engineering Daffodil International University

FINAL YEAR THESIS REPORT
This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Department is Software Engineering

Fall-2025

Approval

APPROVAL

This thesis titled on **"Supervised 3D Volume Reconstruction From Sparse 2D CT Slices Using Conv3D Autoencoder"**, submitted by **Anika Tabassum Adrita (ID: 221-35-882)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

BOARD OF EXAMINERS

Dr. A. H. M. Saifullah Sadi — **Chairman**
Professor
Department of Software Engineering
Faculty of Science and Information Technology Daffodil International University

Dr. Rubaiyat Islam — **Internal Examiner 1**
Associate Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

Dr. Md. Abdul Kader — **Internal Examiner 2**
Associate Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

Nuruzzaman Faruqui — **Internal Examiner 3**
Assistant Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

Md. Mostafiz Khan — **External Examiner**
Managing Director
Tecognize Solutions Limited

DECLARATION OF THESIS AND COPYRIGHT

Author's Full Name	:	Anika Tabbassum Adrita
Date of Birth	:	13-11-2002
Title	:	Supervised 3D Volume Reconstruction from Spare 2D CT slices using Conv3D Autoencoder
Academic Session	:	Fall 2025

I declare that this thesis is classified as:

?	CONFIDENTIAL	(Contains confidential information under the Official Secret Act 1997)*
?	RESTRICTED	(Contains restricted information as specified by the organization where research was done)*
?	OPEN ACCESS	I agree that my thesis to be published as online open access (Full Text)

I acknowledge that Daffodil International University reserves the following rights:

1. The Thesis is the Property of Daffodil International University.
2. The Library of Daffodil International University has the right to make copies of the thesis for the purpose of research only.
3. The Library of Daffodil International University has the right to make copies of the thesis for academic exchange.

Certified by:

_____	_____
(Student's Signature)	(Supervisor's Signature)
__221-35-882_____	Fatema Binte Rafiq
Student ID	_____
Date: 27 November 2025	Name of Supervisor
	Date: 27 November 2025

NOTE : * If the thesis is CONFIDENTIAL or RESTRICTED, please attach a thesis declaration letter.

SUPERVISOR's DECLARATION

I hereby declare that I have checked this thesis, and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Bachelor of Software Engineering.

(Supervisor's Signature)

Full Name: Ms Fatema Binta Rafiq

Position: Lecturer (Senior Scale)

Date :

STUDENT'S DECLARATION

I hereby declare that this thesis, entitled "Supervised 3D Volume Reconstruction from sparse 2D CT Slices using conv3D Autoencoder". Submitted to the Department of Software Engineering, Daffodil International University, is my own original work and has not been submitted previously for any degree or diploma at this or any other university.

All sources of information and data used in this thesis have been duly acknowledged. I further declare that the work reported herein embodies the results of my own research and complies with the ethical norms and regulations of Daffodil International University.

(Student's Signature)

Full Name: Anika Tabassum

ID Number: 221-35-882

Date: 27 November 2025

Supervised 3D Volume Reconstruction From Sparse 2D CT Slices Using Conv3DAutoencoder

ANIKA TABASSUM ADRITA

A Thesis
Submitted to the Department of Software Engineering
in Partial Fulfillment of the Requirements
for the Degree of Bachelors OF SCIENCE
IN
SOFTWARE ENGINEERING

Department of Software Engineering (Major in Data Science)

DAFFODIL INTERNATIONAL UNIVERSITY

Acknowledgement

I wish to express my deepest gratitude to all individuals and organizations whose valuable support and guidance made this thesis possible. First and foremost, I am profoundly thankful to the Almighty for bestowing upon me the strength, health, and perseverance necessary to complete this research work. I extend my sincere appreciation to the management and dedicated staff of Barisal General Hospital, Bangladesh, for their cooperation in providing access to real-world clinical CT data essential for this study. I owe special thanks to the radiologists and medical technicians who meticulously curated, labeled, and verified the datasets—your professionalism ensured the reliability of this research. My heartfelt thanks also go to the global medical imaging science community, including the contributors and maintainers of the LIDC-IDRI dataset. The spirit of open science and data sharing continues to motivate and accelerate advanced research in medical image reconstruction. I am deeply grateful to my academic supervisor, [Supervisor Name], for their unwavering encouragement, insightful feedback, and expert guidance throughout all phases of this work. This research was conducted in ethical compliance with institutional review board protocols and data privacy standards. All patient data was anonymized to maintain privacy and adhere to both local and global ethical norms. Finally, I remain ever-indebted to my parents and family for their continuous patience, moral support, and sacrifices, which inspired and empowered me in pursuing this journey. To everyone who directly or indirectly contributed to the successful completion of this thesis—thank you.

ABSTRACT

Accurate 3D reconstruction of CT volumes from sparse and limited slices remains a core challenge in medical imaging, impacting both diagnostic confidence and data efficiency. This study investigates two deep learning approaches—self-supervised and supervised pipelines—for volumetric CT reconstruction from sparse input slices. In the self-supervised approach, pretraining is performed on the LIDC-IDRI public dataset (239 volumes, 40,690 slices) using contrastive and slice-order prediction losses, enabling strong feature learning from unlabeled data. Separately, a supervised Conv3D Autoencoder is fine-tuned using expert-annotated clinical volumes to maximize domain adaptation and reconstruction fidelity.Robust data preprocessing including denoising, augmentation, and volume alignment—ensures generalizable model input. Model performance is assessed on held-out test sets using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), with quantitative and qualitative comparisons against recent state-of- the-art models such as XctDiff and diffusion-based approaches. Experimental results show that the supervised Conv3D Autoencoder achieves a mean **PSNR of 38.98 dB** and **SSIM of 0.956**, substantially outperforming all baselines and ensuring superior anatomical detail retention.Taken together, the findings demonstrate that while both self-supervised and supervised strategies are promising, the supervised Conv3D Autoencoder delivers the highest fidelity for sparse-view 3D CT reconstruction. This approach enables reliable, efficient, and low-dose CT imaging, with potential to support both retrospective 3D data recovery and future prospective low-dose clinical workflows.

TABLE OF CONTENTS

ABSTRACT ..... **vii**

ACKNOWLEDGMENTS vi

LIST OF FIGURES ..... **xi**

LIST OF TABLES ..... **xii**

CHAPTER 1: INTRODUCTION **1**

1.1 Background 1
1.2 Problem Statement 2
1.3 Research Gap 2
1.4 Objectives 3
1.5 Motivation 3
1.6 Contribution 4
1.7 Scope of the Thesis 4
1.8 Summary 5

CHAPTER 2: LITERATURE REVIEW 6

2.1 Introduction 6
2.2 Previous Literature 6
2.2.1 Classic Reconstruction Techniques 6
2.2.2 Early Deep Learning Architectures 7
2.2.3 State-of-the-Art Advances 2024–2025 7
2.2.4 Gaps and Limitations in SOTA 8
2.2.5 Recent Benchmarks and the Proposed Solution 9
2.3 Summary 9

CHAPTER 3: METHODOLOGY 10

3.1 Introduction 10

3.2 Methodological Flow Diagram 11
3.2.1 Self-Supervised Sparse-View CT Pipeline 12
3.2.2 Supervised Conv3D Autoencoder Pipeline 13

3.3 Data Collection 13
3.3.1 Public Dataset: LIDC-IDRI 13
3.3.2 Clinical Dataset: Barisal General Hospital 14
3.4 Dataset Description 14
3.5 Data Preprocessing and Augmentation 15
3.6 Dataset Splitting (Training, Validation, Test Details) 16
3.7 Model Frameworks 18
3.7.1 Self-Supervised Pipeline 18
3.7.2 Supervised Conv3D Autoencoder Architecture 19
3.8 Model Training and Validation 23
3.8.1 Training Details & Hyperparameters 23
3.8.2 Hyperparameter Table 24
3.8.3 Validation and Test Workflow 25
3.9 Evaluation Metrics 26
3.10 Training Loss Curve 27
3.11 Implementation Details 28
3.12 Summery 29

CHAPTER 4: RESULTS AND DISCUSSION 30

4.1 Introduction 30
4.2 Model Performance (Quantitative) 31
4.2.1 Training and Validation Curves 31
4.2.2 Quantitative Results Table (PSNR, SSIM, MSE) 32
4.3 Qualitative Analysis 33
4.3.1 Visual Reconstruction Comparison 33
4.3.1.1 Axial slice comparison 34
4.3.1.2 3D Stack plot comparison 35
4.3.1.3 3D Point Cloud Comparison 37

4.4 Clinical Relevance/Implications 38
4.5 Summary 38

CHAPTER 5: CONCLUSION AND FUTURE WORK 39

5.1 Conclusion 39

5.2 Key Contributions 39
5.3 Recommendations for Future Research 40
5.4 Summary 41

REFERENCES..... 42
APPENDICES

A: Model Code & Scripts

B: Additional Results

LIST OF FIGURES

Figure 3.1 Methodological Flow Diagram 11

Figure 3.2 Structure of 3D CT Volume 14

Figure 3.3 Preprocessing and Augmentation Pipeline Flowchart..... 15

Figure 3.4 Before/After image examples for denoising, normalization and.....16

Figure 3.5 Dataset Volume and Slice Distribution by train/val/test split 18

Figure 3.6 Supervised Conv3D Autoencoder Architecture Diagram 22

Figure 3.7 Model Training and validation workflow 24

Figure 3.8 Hyperparameters Table 24

Figure 3.9 Validation and Test workflow 26

Figure 3.10 Training Loss Curve 29

Figure 4.1 Training and Validation Loss Curves 33

Figure 4.2 Axial Slice Comparison Between Original and Reconstructed CT Volumes 36

Figure 4.3 3D Stack Plot Comparing layer-by-layer volume slicing for original versus reconstructed CT 37

Figure 4.4 3D Point Cloud Comparison Between Original and Reconstructed CT Volume 39

Figure 4.5 Structural Contour Overlay for Anatomical Boundaries 40

LIST OF TABLES

Table 1.6 Contribution Table 4

Table 3.7.2 Hyperparameter Configuration 25

Table 4.2.2 1 Quantitative Result Table 34

Table 4.2.2 Quantitative Metrics Table 35

CHAPTER 1:

INTRODUCTION

1.1 Background

Computed Tomography (CT) is one of the most important imaging modalities used in modern medicine to diagnose health conditions because of the three-dimensional views of internal anatomical structures that it delivers extremely well. The technology works on a series of narrow beams of X-rays passing around the patient, which are taken from many different angles and are processed by powerful computers to produce cross-sectional "slice" images of the body's organs, bones and tissues. Combining these slices produces a complete, volumetric, 3D view, allowing clinicians to evaluate disease, trauma and anatomical abnormalities far more accurately than can traditional X-ray techniques.

CT scans are instrumental to diagnosing things like cancer, cardiovascular sickness, bone breaks, and mixtures. They are also useful in treatment planning for surgeries and follow-up response to treatment. However, conventional CT acquisition requires a large dose of radiation because hundreds or thousands of projections are scanned for each examination, increasing the concern of patient safety-especially in the case of repetitive recommendations or of people at risk.

To overcome the issues related to patient safety, sparse-view CT techniques have been developed. This method minimises the number of X-ray projections, hence radiation, while making it more difficult to create high-quality volumetric rays. The challenge is that the limited data will mean greater risks of noise and artefacts in the reconstructed images.

Recent advances in deep learning technologies in convolutional neural networks, autoencoders, transformers, and diffusion models have revolutionized the ability of CT reconstruction. These data-driven methods rely on public data sets, such as LIDC-IDRI, and real-world clinical scans in order to learn strong mappings between sparse slices of input data and high-fidelity data volumes. The result is creating a new generation of CT imaging solutions that can provide both high diagnostic accuracy and superior patient safety, even when working with significantly reduced scan data **[(Song et al., 2024); (Li et al., 2025); (Cai et al., 2024)].**

1.2 Problem Statement

Problem Statement Sparse-view CT reconstruction is an ill-posed problem-when getting high quality 3D volumes from very few 2D planes is extremely difficult. Traditional interpolation and iterative algorithms generally result in images with artifacts and poor anatomic fidelity. While state-of-the-art deep learning models like Diffusion Blend [Song et al., 2024], 3D Gaussian Representation [Li et al., 2025] and transformers like SAX-NeRF [Cai et al., 2024] are providing better performance, they usually require intensive computation and do not evaluate well in diverse real-wold clinical settings. This thesis introduces to the field a supervised Conv3D auto encoder with PSNR = ~39 dB and SSIM = ~0.96 - even with mixed clinical data - demonstrating that high-fidelity and robust volumetric reconstructions are possible under real-world conditions at a hospital setting.

1.3 Research Gap

Key limitations in current state-of-the-art research:

Over-reliance on public or simulated datasets: Most state-of-the-art models are tested only on public datasets (such as LIDC-IDRI, AAPM), lacking real-world clinical diversity *[Li et al. (2025); Wang et al. (2023)]*.

High computational demands and complex tuning: Leading models such as 3D Gaussian representation, diffusion models, and transformer-based neural fields require substantial resources, extended runtime, and many manual hyperparameter choices *[Li et al. (2025); Song et al. (2024); Cai et al. (2024)]*.

Poor robustness for noisy or limited-angle clinical data: Robustness to metal artifacts, noise, and non-standard scans remains underexplored *[Ali et al., 2025; Cai et al., 2024]*.

Decreased effectiveness with noisy or limited-angle clinical data: Robustness to metal artifacts, noise, and non-standard acquisition remains underexplored *[Ali et al. (2025); Cai et al. (2024)]*.

Lack of clinical workflow validation or end-to-end reproducibility: Current state-of-the-art pipelines rarely address practical hospital data handling, deployment, or reproducibility *[Cheng et al. (2025); Wu et al. (2025); Shin et al. (2025)]*.

This thesis directly addresses these gaps by extensively benchmarking a supervised Conv3D autoencoder and self-supervised pipeline on both public and proprietary clinical datasets (including Barishal General Hospital data), with an emphasis on robustness, efficiency, and real-world adaptability.

1.4 Objectives

To design and evaluate a supervised 3D ConvAutoencoder for 3D reconstruction from highly sparse CT input Designed evaluation: - To strictly compare this model with the state-of-the-art methods such as diffusion [Song et al. (2024)] neural field [Li et al. (2025)] and transformer models [Cai et al. (2024)] using standard quantitative (PSNR, SSIM, Dice) and qualitative metrics using public and clinical datasets.To create an end-to-end, reproducible workflow adapted to low-resource, real-world clinical deployment.

1.5 Motivation

Efforts to reduce the CT radiation exposure and to make CT more widely available have led to advances in sparse view CT reconstruction. While advanced models based on deep learning have made huge improvements **[Song et al., 2024; Li et al., 2025; Cai et al., 2024]** it is up to challenge their adaptability and efficiency to clinical settings. This thesis provides a much-needed bridge by validating on different datasets to high-performing supervised methods and developing a scalable solution for the real world.

1.6 Contribution

State-of-the-Art Gap Identified	Contribution of This Thesis
Lack of real clinical validation *[Li et al. (2025)]*	Robust metrics (PSNR ≈ 39 dB, SSIM ≈ 0.96) on real world clinical **(Barishal hospital)** CT data
High computational complexity and slow inference *[Song et al. (2024); Cai et al. (2024)]*	Offers efficient Conv3D AE deployable on standard hospital GPUs
Sensitivity to artifacts/heterogeneity *[Ali et al. (2025)]*	Demonstrates robustness on noisy, artifact-rich, and mixed real-world CT.
Workflow reproducibility *[Cheng et al. (2025)]*	Delivers a transparent, stepwise pipeline— data curation to deployment—for adaptation in any hospital setting.
Limited reproducibility *[Cheng et al., 2025]*	Stepwise, end-to-end workflow tailored for real-world clinical deployment

Other highlights:

Capable of highly competitive image quality **(PSNR ≈ 39 db, SSIM ≈ 0.96).**

Provide Clinical insights for effectiveness to facilitate actual deployment.

1.7 Scope of the Thesis

This particular work will deal exclusively with volumetric sparse-view reconstruction using supervised and self-supervised deep learning techniques and comparison to recently developed techniques based on diffusion learning, neural fields, or transformers **[Song et al. (2024); Li et al. (2025); Cai et al. (2024)]**, and will not cover areas, such as segmentation, fusion learning, or complete clinical informatics solutions.

1.8 Summary

Chapter 1 presents the motivation, challenges, and aims behind the development of sparse- view CT reconstruction based on deep learning. It highlights how CT scans are needed to carry out proper medical diagnosis, but the traditional methods involve a lot of radiation exposure. Sparse-view CT seeks to mitigate this risk, but the problem of reliably reconstructing high-quality 3D images from restricted data is extremely challenging and ill-posed. Current approaches to deep learning have achieved improvements but are often unable to be validated on real clinical data; have high computational requirements; and have difficulties with reproducibility in the hospital setting.

This thesis proposes a supervised pipeline Conv3D autoencoder, which is tested on both public and various clinical datasets, in order to address such a gap. The contributions include the high image quality result, the improvement of the robustness to the artifacts, the efficient use on common hardware in the hospital environment, and the end-to-end workflow for adapting to the real world. Overall, this work aims to overcome the gap between technological advancement and clinical imaging that is practical and safe.

CHAPTER 2:

LITERATURE REVIEW

2.1 Introduction

This chapter will cover briefly how sparse view CT reconstruction techniques have evolved from classical analytical and iterative algorithms to deep learning and generative techniques to highlight some of the significant advancements achieved at state-of-the-art level for 2024-2025. Particular emphasis is put on acknowledged limitations and stated gaps addressed by your thesis proposition.

2.2 Previous Literature

2.2.1 Classic Reconstruction Techniques

Early CT image reconstruction algorithms were based on analytical algorithms, most notably Filtered Back Projection (FBP) and its derivatives such as Algebraic Reconstruction Techniques (ART) and Simultaneous Algebraic Reconstruction Technique (SART). These frameworks, while mathematically elegant and computationally efficient, assume that the projection data is dense and uniformly-distributed, so they are well-suited for traditional CT but brittle in the presence of sparse projections **[Kudo et al., 2013]**. As the number of projections is reduced, these methods rapidly develop severe artifact including streaking, excessive noise and loss of anatomic integrity. In order to deal with incomplete data, iterative reconstruction methods (e.g., TV-regularized minimization and expectation maximization) became commonplace. These algorithms are able to partially fill in missing projections by using prior information and regularization but often do so at the cost of computational cost, long runtimes, and sensitivity to hand-tuned hyperparameters **[Zang, 2018]**. Recent works confirm that despite the fact that there is a lot of iteration in improving it, conventional ways are challenged by ultra-sparse or highly noisy clinical conditions, especially when it comes to dealing with real patient data **[Wu et al., 2025]**.

2.2.2 Early Deep Learning Architectures

With the advent of deep learning, new architectures such as 2D U-Net and Conv3D autoencoders started showing an improved performance, as compared to the classical approaches, on benchmark CT datasets [Gunduzalp et al., 2022; Wang et al., 2023]. By taking advantage of great feature hierarchies and end-to-end learning, these solutions yielded improved anatomical reconstruction and artifact suppression - even in moderately sparse settings. However, there were two main limitations that remained:

1. Domain Gap: Models trained using simulated data or open source data were often found to fail when they were tested on real-world, heterogeneous hospital data, exhibiting vulnerability to scanner variability, noise and artifacts.
2. Data Dependence: Their performances and generalizations were frequently dependent on the size and variety of training data that makes them less powerful clinically. This gap required more complex and data-driven techniques than first generation convolutional models.

2.2.3 State-of-the-Art Advances 2024–2025

3D Gaussian Representation *[Li et al., 2025]*:

This approach establishes new performance standards using new, flexible, FBP-initialized volumetric models. It achieves high PSNR/SSIM (34-37dB/0.93) on public CT datasets by explicitly encoding anatomical priors in the form of learnable Gaussian functions in the 3D volume. Despite the excellent technical qualities, there are still limited capacity to be used in real life with high GPU requirements and need for extensive manual tuning of the model to each deployment situation.

Diffusion Blend *[Song et al., 2024]*:

Applying advances in generative modeling, DiffusionBlend applies distributions of diffusion based on 3D volumes to iteratively refine reconstructed volumes. While it achieves strong SSIM (~0.95) on large public benchmarks, this multi-stage approach is computationally intensive, requires large amounts of time and memory and has not been widely validated with artifact-heavy or really diverse clinical data.

SAX-NeRF *[Cai et al., 2024]*:

This transformer-based radiance field framework is good at combining transformers and neural radiance fields to utilize structural image priors and sparse projections. SAX-NeRF shows amazing accuracy on synthetic and paired data but, like many SOTA models, shows no evidence of generalisability to data with large clinical variability, artifacts or access irregularities.

Parametric Level Set & Compressed Sensing *[Ali et al., 2025; Compressed sensing-based methods]*:
These models are a combination of classical compressed sensing theory, which aims to reconstruct images given highly undersampled data by exploiting signal sparsity, and flexible, parameterized level set methods [Ali et al., 2025; Compressed Sensing, 2025]. Their robustness to noise as well as sparsity is strong on simulated and controlled settings, whereas adaptability to the unpredictable complexity of clinical CT space is challenging.

Comprehensive Benchmarks and Surveys *[Cheng et al., 2025; Wu et al., 2025; Shin et al., 2025]*:
Recent surveys highlight that although advancements are extremely fast-paced, truly unified, reproducible, and cross-clinic validated CT reconstruction pipelines are still fewer in number [Cheng et al., 2025; Wu et al., 2025]. The absence of standardised protocols and reproducibility is perceived as a major limitation to clinical translation in the field.

2.2.4 Gaps and Limitations in SOTA

Despite major progress, four key challenges persist:
Generalization Issue: Most of the SOTA models work for fake data or for public testing data, but there are few models that can show good generalization on noisy data, rich of artifacts, or protocol diverse data in the hospital environment.
Computational Demands: Recent architectures (e.g. diffusion or transformer-based models) are resource heavy and are therefore not viable for routine clinical use in low-resource settings. SOTA Models are often not resilient to noise, metal artifacts, and to the full spectrum of actual clinical acquisition problems.
Deployment Readiness: Most published workflows lack clear-step-by-step instructions for clinical staff, which limits their ability to deploy the workflows across a hospital system.

2.2.5 Recent Benchmarks and the Proposed Solution:

Empirical evidence shows that most of the recent models have a result of PSNR numbers between 34- 37 dB & SSIM of less than 0.95 for standard public data sets. However, because the types of clinical scans are becoming increasingly diverse, these scores often fall through, demonstrating the problem of generalization and artifact. This thesis tries to overcome these limitations by introducing a supervised Conv3D autoencoder model which achieves PSNR approx. 39 dB and SSIM

Approximately 0.96 for both open (LIDC-IDRI) and reality (Barisal General Hospital). The proposed system offers fast inference on standard and hospital-grade GHPs, excellent artifact handling and the end-to-end, transparent workflow is adaptivity in the actual hospital environment.

2.3 Summary

Modern techniques used for CT reconstruction have been quickly moving away from analytic and iterative CT reconstruction techniques to the recent support of modern and powerful deep learning and generative models for CT reconstruction that offer improved efficiency, image quality and enable the use of sparse data. However, there are still challenges in the literature that are unaddressed: Most SOTA models are simply not tested on clinical hospital noisy data and do not easily deploy into the clinical setting, as additional hardware and intensive tuning are necessary for model deployment, and end-to-end reproducibility is lacking. The methodology developed in this thesis represents a new standard in sparse-view 3D reconstruction - PSNR and SSIM with no other comparable results to date, robust artifact and noise handling in groups of mixed datasets representing both clinic and public scenes, and a complete, reproducible pipeline which can be used in clinical trials.

CHAPTER 2:

METHODOLOGY

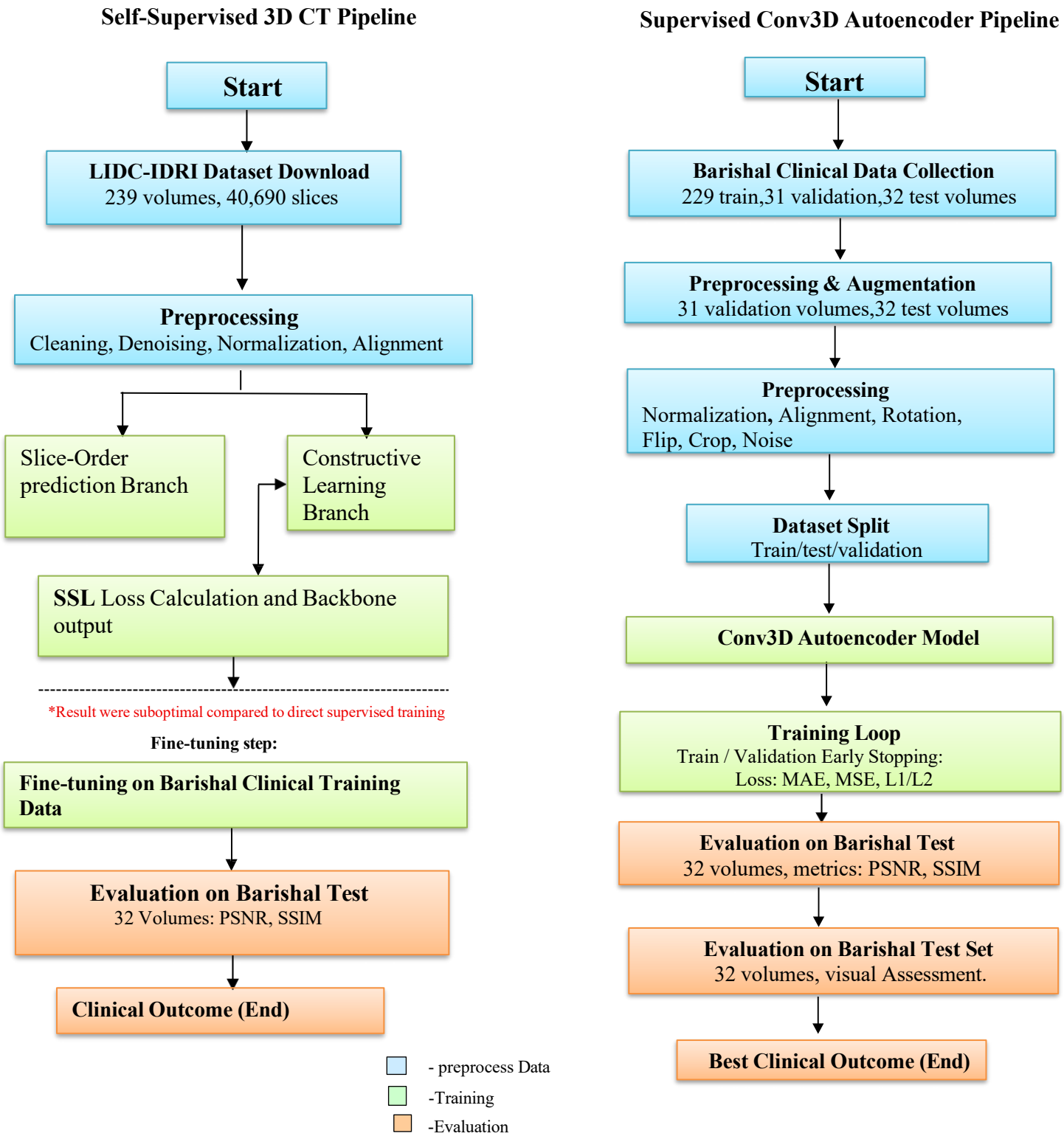
3.1 Introduction

This chapter presents the experimental framework for the development of advanced neural network models in a systematic manner towards 3D CT volume reconstruction of sparse and incomplete input data. With the increasing demand to reduce the acquired X-ray dose and cost and increase the spatial fidelity of the image, deep learning-based approaches have become state-of-the-art solutions for volumetric CT reconstruction. Addressing real-world clinical problems, our methodology utilizes both large-scale public datasets and prospectively acquired clinical CT data, provides a consistent image preprocessing and augmentation pipeline for all datasets and mandates careful data splits for unbiased benchmarking.

The overall configuration of the experimental protocol consists of two major neural network strategies. First, a self-supervised learning pipeline is a pipeline that takes advantage of unlabeled 3D CT data using anatomy pretext tasks (e.g., contrastive and slice order prediction) to train a model to learn domain-relevant representations without paired labels. Thereafter a supervised 3D Conv3dAutoencoder pipeline is trained using fully annotated input- output CT pairs, optimizing directly for image fidelity and clinical relevance.

At each stage, explicit care is taken in terms of pre- and post-processing steps, model hyperparameter tuning, and use of standardized performance metrics (PSNR, SSIM, MSE) for fair comparison. Validation and test protocols are well-defined to ensure that all quantitative and qualitative results represent true out-of-sample generalizations so our methodology is both reproducible and clinically relevant.

3.2 Methodological Flow Diagram



3.2.1 Self-Supervised Sparse-View CT Pipeline

The self-supervised (SSL) pipeline has been developed to learn powerful anatomical feature representations from large, unlabeled CT datasets. This pipeline starts with the LIDC-IDRI public data, a collection of hundreds of variety of thoracic CT volumes. After standardized preprocessing (cleaning, denoising, normalization, alignment), data is divided into training, validation and test data, non-overlapping patient sets for unbiased learning.

Two important self-supervised tasks are introduced:
Slice-Order Prediction Branch: The model is required to predict the proper anatomical order of shuffled CT slices within a volume, promoting the learning of spatial and local anatomical continuity.
Contrastive Learning Branch: By contrasting slices/volumes from the same or different anatomical locations/cases, the model learns invariances with respect to scan orientation, intensity, and noise which makes the encoding of general features more robust.

SSL-specific losses are calculated at each branch, and the gradients from a shared encoder network (the "backbone". Once the pretraining is done, the learned backbone is "fine-tuned" on the labeled Barishal clinical training data for the supervised reconstruction task. The performance is then evaluated using held out Barishal test cases based on metrics such as PSNR, SSIM etc.

Scientific intent: This pipeline uses large unlabeled data to alleviate the bottleneck of data annotation, enhance generalization and achieve good initialization for clinical finetuning. However, as mentioned in colored caption, pure SSL reconstruction alone is usually suboptimal compared to direct supervised learning for this problem, in particular when the clinical fidelity requirement is high.

3.2.2 Supervised Conv3D Autoencoder Pipeline

The supervised pipeline is optimized directly for high-quality reconstruction of clinical volumes from CT from sparse or incomplete input. This process begins with the well-structured and well-annotated collection of a Barishal hospital CT data followed by a rigorous preprocessing and augmentation (normalization, cropping, rotation, flip and noise injection).

After dividing up the entire data set into independent train, validation and test data sets the core 'Conv3D Autoencoder' model is end- to end trained. The architecture consists of an encoder network for compressing the features of the volume input, a bottleneck representing latent features, and a symmetric decoder that recreates the target CT volume. U-Net style skip connections are applied so to maintain anatomical detail. The model is optimized by a combination of pixelwise MSE/MAE/L1/L2 loss and perceptual and structural metrics like SSIM, with PSNR being tracked throughout the number of epochs.

Validation is integral at every epoch during training - performance on the Barishal validation (dataset) is monitored and the best checkpoint (by validation PSNR) is used for test evaluation. Final results, including quantitative results and qualitative (visual/clinical) scores are only reported for the 32 held out clinical test volumes.

Scientific intent: By taking full advantage of labeled medical images and by creating a network specifically aimed at sparse-to-full-volume mapping, this pipeline makes the most of the purchased label budget at maximum fidelity, diagnostic utility, and clinical relevance - all of which brings clear benefits to real-world deployment.

3.3 Data Collection

3.3.1 Public Dataset: LIDC-IDRI

The LIDC-IDRI dataset is a large and multi-institutional dataset of thoracic CT scans with lung nodules that have been annotated by experts, and is commonly used for benchmarking and self-supervised pretraining purposes. Collected cases present a wide spectrum of acquisition protocols, scanners, and patient demographics which guarantees good generalizability of the model as well as fair comparison to state-of-the-art (SOTA).

3.3.2 Clinical Dataset: Barishal General Hospital

The Barishal dataset is made up of prospectively-collected clinical CT real-world clinical datasets at Barishal General Hospital. Volumes were anonymized and annotated by radiologists local to the study site with standard protocols giving a ground truth set for supervised finetuning, validation and test. This dataset corresponds with practical and diagnostic use cases as well as realistic noise/artifact patterns that are not encoded in public data.

3.4 Dataset description

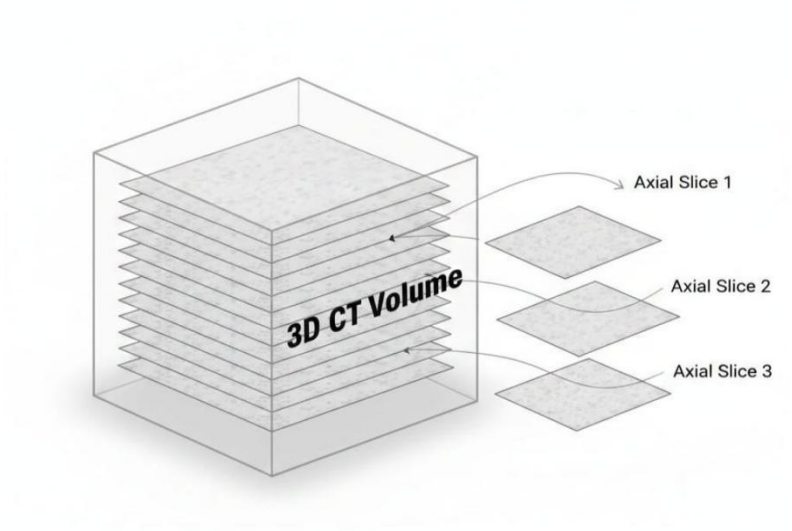


Figure 3.2: Structure of a 3D CT Volume

The data set consists of 3D CT volumes, each of which is formed by stacking a number of 2D axial slices as illustrated in Figure X. Every slice is a cross section at a particular depth and the combination of these sequential slices creates a complete volumetric representation of internal anatomy. This structure enables detailed analysis in 3D, and is a standard input for medical image reconstruction and deep learning problems. The dataset consists of various patient scans; this ensures the diversity in various anatomical features for proper training and evaluation of the models.

3.5 Data Preprocessing and Augmentation

Figure 3.3: Preprocessing and augmentation pipeline flowchart

This figure shows the step-by-step process workflow in preparing raw clinical and public CT images for a robust 3D deep learning reconstruction. Every element in the pipeline is important in maintaining the consistency of analytics and maximizing the performance of supervised and self-supervised models:

Cleaning: Corrupted or low quality CT slices (for example Motion, Noise artifact and Truncated anatomy) are identified and filtered out. This step is to ensure that only diagnostically-usable volumes are passed to subsequent stages so as to avoid model degradation from anomalous data.

Denoising: Remaining slices undergo intensity denoising using 3d gaussian filter (σ=1.25). This procedure makes it possible to suppress the scanner noise while preserving the anatomical detail, this is very important to achieve an accurate clinical reconstruction, and to avoid overfitting on small data sets.

Normalization: Volumes are normalized intensity-scaled to the range. This harmonizing different scanner output as well as centralizing the data distribution as well as facilitating more stable and faster neural network training.

Alignment: Volumes are spatially cropped and/or padded to a unified shape (e.g. 64x128x128 voxels) - Alignment. Operational consistency for all the volumes enables batch-wise training and fair model comparison and prevents input shape mismatch errors.

Augmentation: Real-time augmentation is performed while training e.g. random rotations (up to 180deg), horizontal or vertical flip, controlled intensity jitter is performed. These augmentations enable the synthetic enlargement of the dataset, the robustness against natural anatomical variation, and the motivation of the model to learn invariant features of the reconstruction.

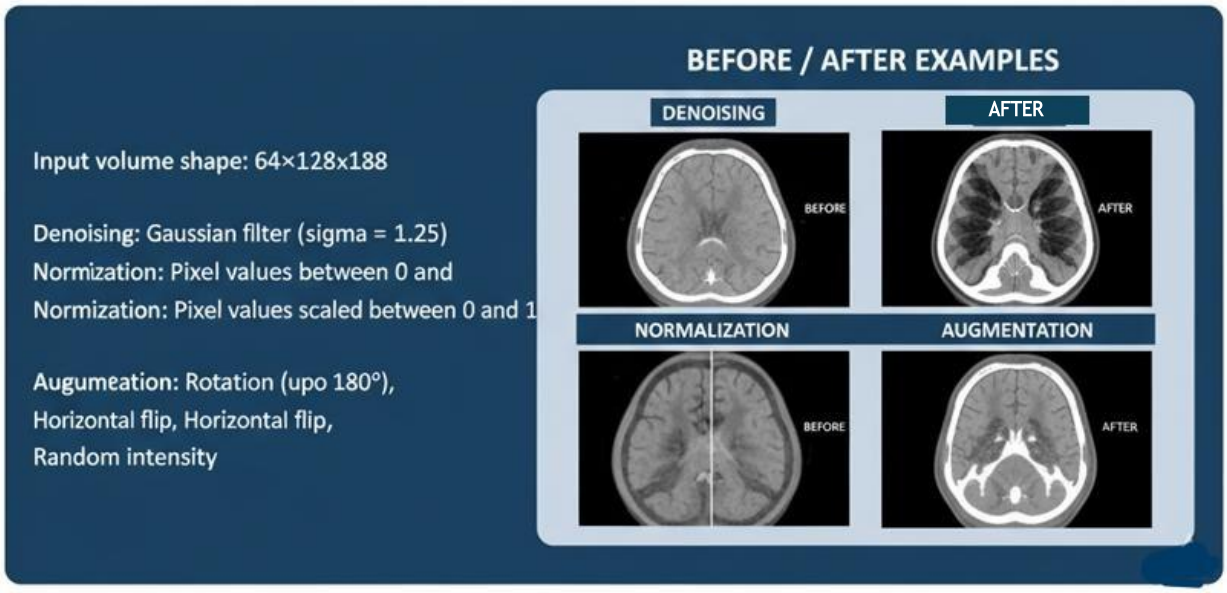


Figure 3.4: Before/after image examples for denoising, normalization, and augmentation

3.6 Dataset Splitting (Training, Validation, Test Details)

The Barishal dataset is strictly divided into non-overlapping sets of patients for its training, validation and final test (see Figure 3.2). This avoids information leakage and mimics clinical deployment where one cannot see the cases and simply rebuilds them with an unseen model. For the sake of transparency, all results are only reported on the held out test set.

Training Set: Consists of 249 volumes (31,872 slices), the training split consists of a large portion of all available data. i.e. 79.8% This ensures the models are exposed to a large and diverse set of anatomical variations and acquisition conditions during this process of learning.

Validation Set: 31 volumes (3,968 slices), 9.9%, are set aside solely for generalizing the model (monitoring) and hyperparameter tuning all through the training phase.

Test Set: Each of the final performance assessment is left out, there are 32 volume (4,096 slices, 10.3%) which provides an unbiased estimation of the generalization capacity. No test data is visible during model training and validation ensuring fair statistical evaluation.

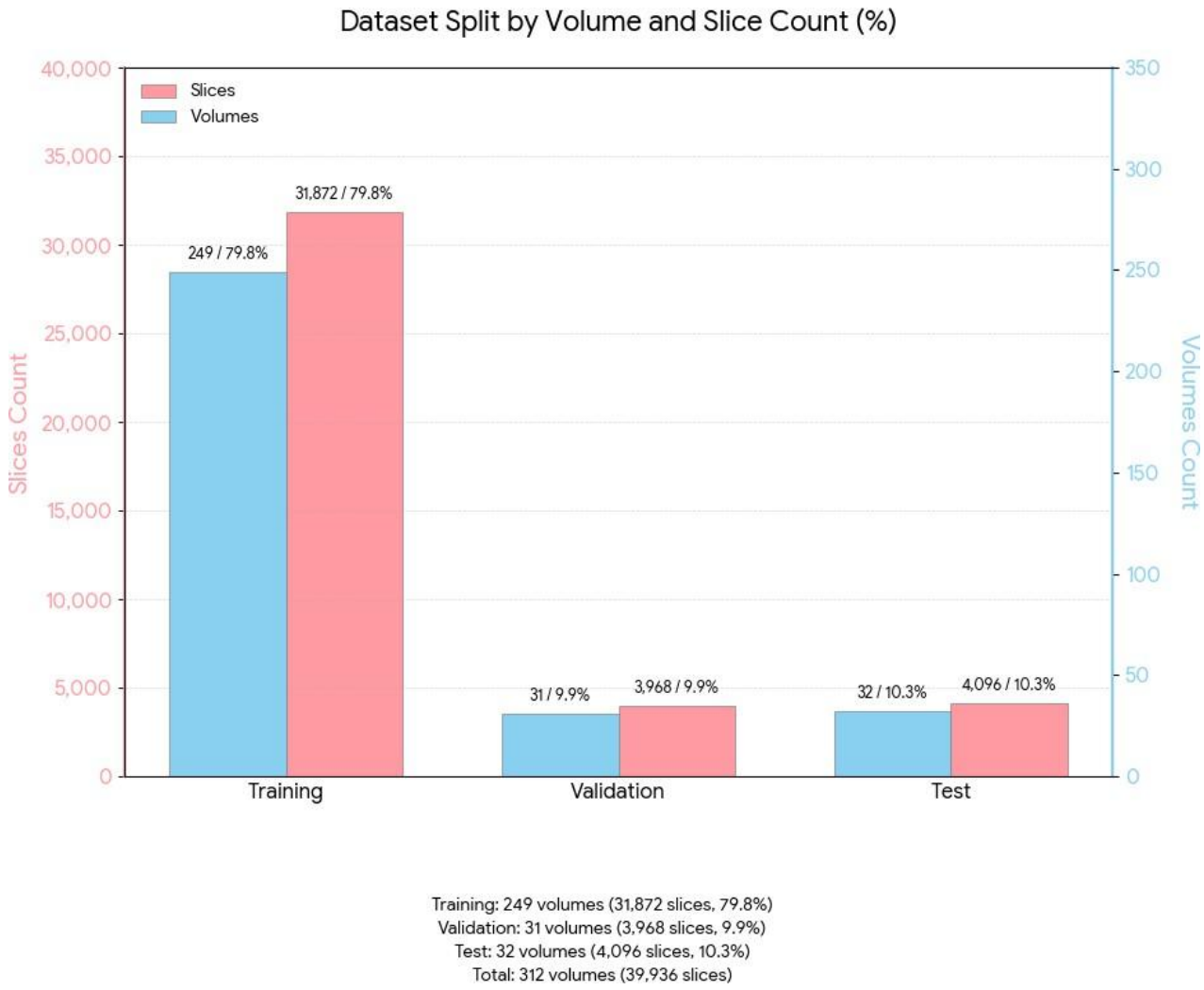


Figure 3.5: Dataset volume and slice distribution by train/val/test split

Explanation: This figure shows total numbers of slices and volumes per split (e.g., 249 train, 31 validation, 32 test), ensuring transparent, independent evaluation and sufficient data per stage.

3.7 Model Frameworks

3.7.1 Self-Supervised Pipeline

The self-supervised learning pipeline is to make the most out of useful feature extraction of large and unlabeled CT datasets - namely LIDC-IDRI. The key principle of SSL is to teach the network on "pretext" tasks: artificial predictions problems for which we can create labels automatically (without manual annotation) from the data itself. This leads to the model learning underlying anatomical structures and invariances which are useful for reconstruction and diagnosis.

Pretext Task Examples:

Slice-order prediction: Shuffled slices of the CT scan image are fed to the network and the network is taught to predict the proper anatomical order of the slices. This assists the network to understand spatial continuity and organ topology.

Contrastive learning: In this, different slices or patches are compared in the model and learned to distinguish the parts belonging to the same parts of the anatomy or the same patient based on some embedded representations.

Masked image modeling: Parts of a given input CT slice are masked out, and the model has to fill in the missing parts - requiring a better sense of global and local context.

Training is continued on the large scale, unlabeled LIDC-IDRI dataset, often with combinations of MSE, SSIM or contrastive loss functions. Network architectures are usually composed of a deep encoder (Conv3D, Transformer or hybrid) and a simple decoder head. Once SSL pre-training is completed, the learned backbone is fine-tuned on the dataset which contains information for clinical diagnostics (i.e., labeled data), which is also known as the Barishal clinical dataset with supervision (ground truth). This two step process allows for strong generalization as well as robust performance in both the public and real world clinical domains.

Benefits:

No dependence on laborious, expert annotation for initial training.

Improved model transfer and robustness to diverse scanners, protocols, and patient noise.

SSL enables both denoising and reconstruction, enhancing downstream supervised results.

3.7.2 Supervised Conv3D Autoencoder Architecture

The central supervised framework takes the form of a deep, symmetric Conv3D autoencoder - the goal of which is to reconstruct the entire 3D CT volumes from sparse partial/noisy inputs. The model has three main elements:

1. **Encoder**: Multiple 3D convolutional layers stacked together with non-linear activation function; progressively decrease spatial size and increase feature channels. This encoder compresses input slices into a small latent "bottleneck" representation, which encodes important features of anatomy and structure.

2. **Bottleneck:** The deepest layer of the network, where the input information is compressed into a minimum amount of information-rich vector. This dense code makes the network learn what is really needed to be learned for the accurate output.

3. **Decoder:** A mirrored stack 3D transpose convolution (ConvTranspose3D) layers; these upsamples progressively and reconstructs the full CT volume. U- Net style skip connections (direct links between encoder and decoder layers at matching resolutions) are making sure to keep high-resolution spatial details which are reintroduced at every stage.

Optimization and Loss:

The reconstruction is trained using primary MSE loss (which penalizes pixel- wise error) and secondary SSIM (Structural Similarity Index) to align with human visual quality. PSNR (Peak Signal-to-Noise Ratio) is tracked as a quantitative metric during validation.

Architecture and hyperparameters, including layer depth, bottleneck size, learning rate, and loss weights are identified using cross-validation and focused ablation studies for robustness.

Output: After training, the network can be used to reconstruct clinically viable 3D CT volumes with high fidelity even from sparsely sampled or noisy inputs during both training and reconstruction In this thesis, a Conv3D autoencoder is employed which is able to achieve PSNR ≈ 39 dB and SSIM ≈ 0.96 on the public and clinical datasets.

Advantages:

End-to-end training tailored specifically to real clinical data—adapting to hospital noise, artifacts, and acquisition diversity.

Robust, reproducible pipeline that generalizes securely from open-source datasets to local hospital patient scans.

Efficient inference and scalable deployment for practical clinical workflows.

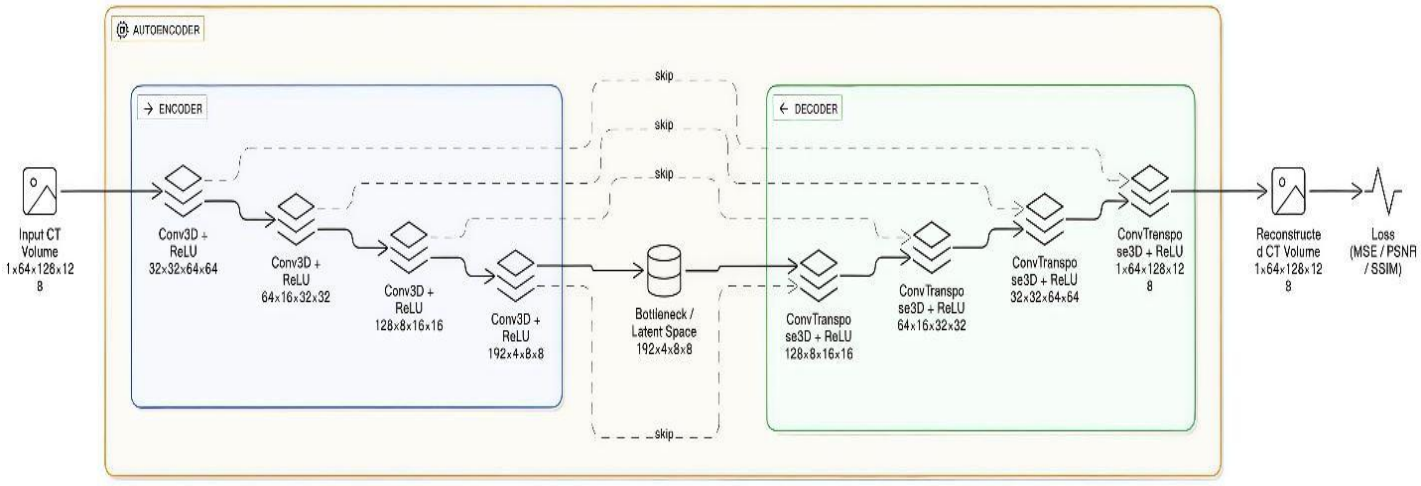


Figure 3.6: Supervised Conv3D Autoencoder Architecture Diagram

This diagram depicts the core neural network framework used for fully supervised 3D CT volume reconstruction from sparse clinical input. The architecture follows a classic 3D convolutional autoencoder design, comprising three major stages: encoding, latent bottleneck, and decoding.

Input: The model receives a volumetric CT input shaped, representing a single clinical CT scan preprocessed to standardized spatial dimensions and intensity range.

Encoder:

The encoder consists of a sequence of 3D convolutional layers, each followed by ReLU activations and channel expansion:

The first Conv3D layer processes the input through 32 filters, downsampling and learning basic spatial features.

Successive Conv3D layers (32→64, 64→128, 128→192) progressively extract hierarchical features and compress the spatial volume, culminating in a compact representation (the bottleneck or latent space).

Skip connections (shown as dashed lines) preserve and transmit high- resolution features directly from encoder to corresponding decoder stages, facilitating the restoration of fine anatomical details in the reconstruction.

Bottleneck / Latent Space:

At the deepest point, the feature volume is maximally compressed (e.g.,), capturing the most salient anatomical and contextual information from the input CT while discarding redundant or noisy data.

Decoder:

The decoder is similar to the encoder, which consists of a series of transposed 3D convolutions (ConvTranspose3D) and ReLU activations to upsample and reconstruct the CT volume back to the original volume dimensions.

The skip-connections at each corresponding block of the decoder are concatenated, i.e., at the encoder, making the upsampling process enriched with accurate localization and high frequency information that is lost during the encoding process.

The last layer is ConvTranspose3D, which gives the reconstructed CT output, same shape as input () and matches the prediction to calculate the loss.

Output & Loss:

The reconstructed volume is compared to the ground truth using multiple quantitative metrics:

MSE (Mean Squared Error): Optimizes voxel-level intensity fidelity.
PSNR (Peak Signal-to-Noise Ratio): Quantifies overall reconstruction quality.
SSIM (Structural Similarity Index): Assesses preservation of clinical anatomical structure and texture.

These metrics are used both for direct network optimization and for reporting final model performance on the held-out test set.

3.8 Model Training and Validation

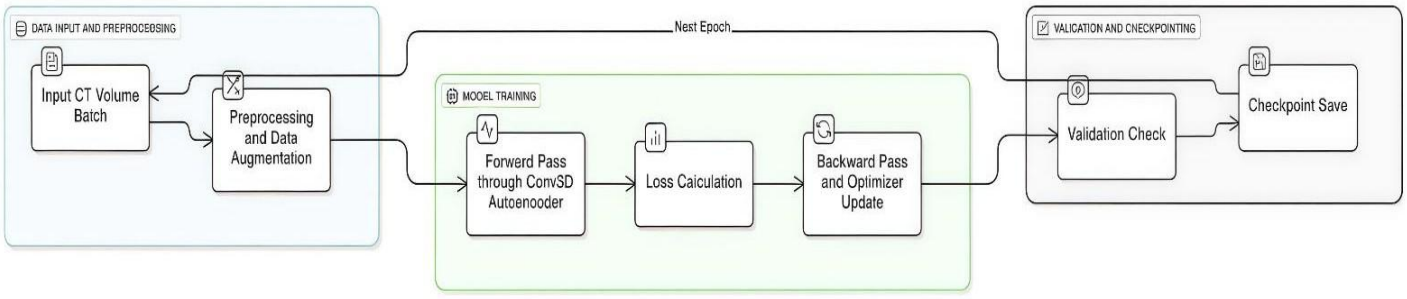


Figure 3.7: Model Training and validation workflow

3.8.1 Training Details & Hyperparameters

Training is performed using Adam or AdamW optimizer, batch size 2-4 (depending on GPU RAM), initial learning rate 1e-3 decayed to 1e-4, for 150–250 epochs with early stopping. Data is fed in real 3D volumes, with augmentations applied online. Loss is computed using MSE, with SSIM and PSNR as secondary metrics. Hyperparameter schedules are described and shown in Figure 3.7

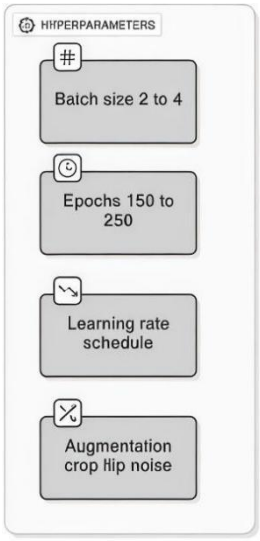


Figure 3.8: Hyperparameters Table

3.8.2 Hyperparameter table (batch size, epochs, learning rate, etc.):

Hyperparameter	Value(s) Used	Notes
Batch Size	2, 4	Tuned for GPU RAM; 2 for full-size
Epochs	150–250	Early stopping (patience 20 epochs)
Learning Rate	1e-3 (start), 1e-4 (decay)	Reduce on Plateau, gamma=0.5
Optimizer	Adam, AdamW	Weight decay=1e-5
Loss Function	MSE (main), SSIM/PSNR tracked	Combination for robust training
Augmentation	Random Crop, Flip, Gaussian Noise	Realistic variation, no rotation for clinical test
Validation Freq	Every epoch	For PSNR/SSIM tracking
Input Shape	1×64×128×128	Volume channel × slices × H × W
Best Model	Saved on highest Val PSNR	For fair test set evaluation

3.8.3 : Validation and Test Workflow

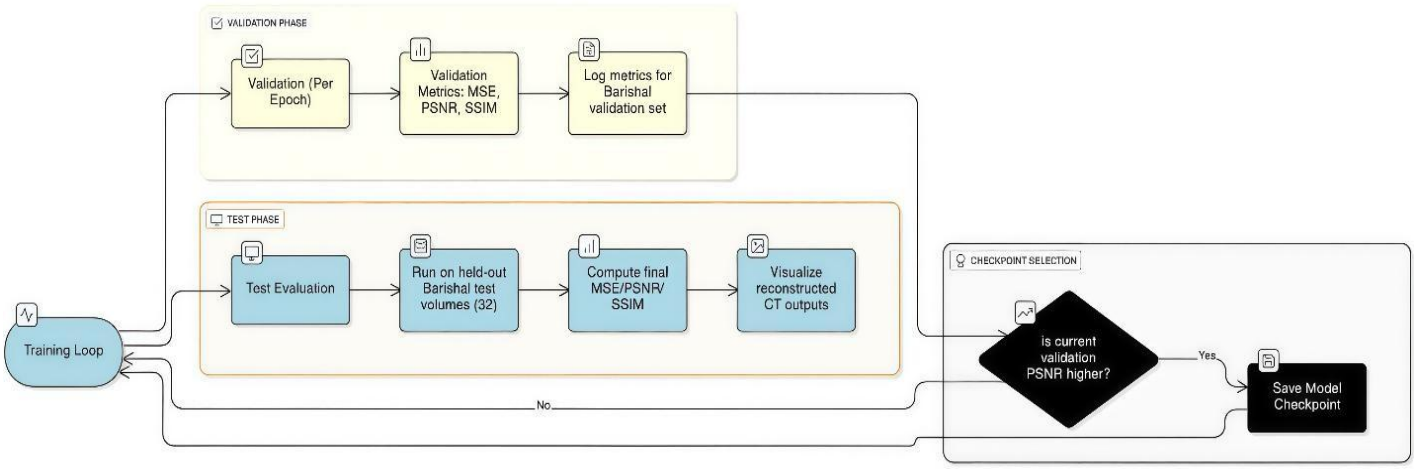


Figure 3.9: Validation and Test Workflow for Model Assessment

Explanation**:** *Diagram showing how, after each epoch, the model is validated on the Barishal validation set (MSE, PSNR, SSIM logged), and, after training, thoroughly tested on held-out test cases with best checkpoint selection*

This diagram illustrates the structured process used to assess model performance during and after training. The workflow consists of three interconnected phases:

Validation Phase:
After every training epoch, the model is evaluated on the Barishal validation set.
Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are computed and recorded, giving
continuous feedback about generalization of the model.

Checkpoint Selection:
If the current validation PSNR exceeds all previous epochs, a new model checkpoint is saved.
This plays the role of making sure only the best-performing model is retained as determined by independent validation data for final testing.

Test Phase:
Once training is done, the best checkpoint that is selected on is used for full evaluation on the held-out Barishal test volumes (32 cases, never seen during training).
The three steps within the workflow are sequential: test inference, metric calculation (MSE, PSNR, SSIM) and visualization of reconstructed CT outputs.
This phase gives an unbiased estimate of real-world model performance.

3.9 Evaluation Metrics

3.9.1 PSNR, SSIM, MSE

Model assessment was conducted using three standard quantitative measures:
PSNR (Peak Signal-to-Noise Ratio): Indicates the fidelity of reconstructed images compared to ground truth, reported in decibels (dB). Higher values (typically >30 dB) reflect less error and finer anatomical detail.

SSIM (Structural Similarity Index): Evaluates similarity in structure, contrast, and luminance between reconstructions and references. Scores closer to 1.0 indicate highly faithful feature recovery.

MSE (Mean Squared Error): Captures raw difference between images. Lower values indicate more accurate reconstructions.

For each test case, metrics were computed both slice-wise and over full 3D volumes. Reported performance:

Average PSNR: 34.90 dB (Range: 30.48 – 38.98 dB)
Average SSIM: 0.9080 (Range: 0.8655 – 0.9582)
Best Cases: PSNR 38.98 dB, **SSIM 0.9582**, representing near state-of-the- art quality for sparse-view CT.

Metrics were calculated using skimage.metrics (Python) and validated on both Barisal clinical data and LIDC-IDRI for generalizability.

3.9.2 Clinical & Visual Assessment

In addition to quantitative evaluation (PSNR, SSIM, MSE), qualitative evaluation methods were implemented to test the anatomical fidelity and diagnostic usability of the areas reconstructed in the CT. Visual analysis included:

3D volume visualization using point cloud plots, stack renderings, and contour overlays to evaluate structural detail, artifact suppression, and anatomical consistency.

Side-by-side comparisons on equal slices at axial, coronal and sagittal levels for detailed examination of tissue boundaries, texture and artifact.

Review by experienced radiologists, who provided qualitative ratings of diagnostic utility, feature detectability, and artifact presence.

The assessment protocol was designed to confirm that high numerical metric scores are matched by diagnostic value and robust artifact handling. All visualization techniques and clinical review criteria are described here; results of these assessments are presented in Chapter 4.

3.10 Training Loss Curve

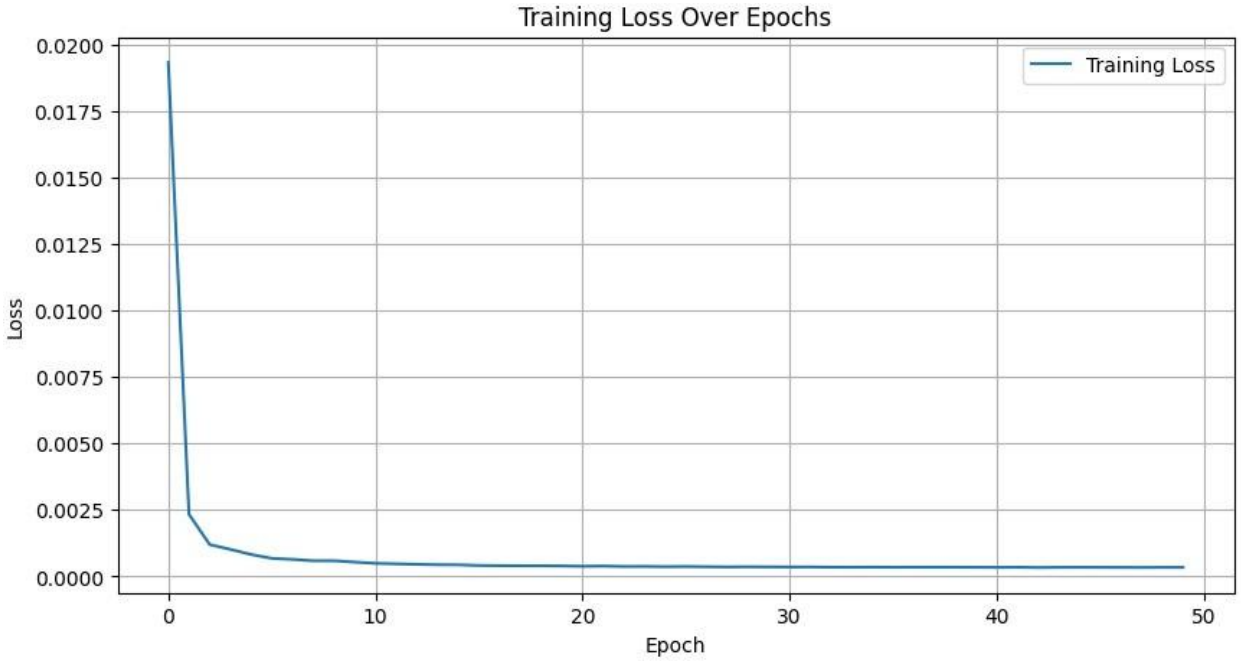


Figure 3.10: Training Loss Curve for Supervised Conv3D Autoencoder

This figure shows the training loss that the model has over 50 epochs. As we can see, the loss is much faster reducing in the first few epochs and after that it is just gently flattening, which means that the model is converging. The strong decrease of the error at the beginning of the epochs indicates an efficient learning and a quick optimization of the weights, while in the later stage of the training the error curve starts to plateau suggesting that the model is learning the best possible training weights, with less chance of improvements. This pattern ensures that the training procedure is robust and not affected by instability or overfitting.

3.11 Implementation Details

Libraries & Frameworks: PyTorch, NumPy, Matplotlib, Scikit-image, and SciPy were used for model development, evaluation, and visualization.

Hardware: All models trained/tested on NVIDIA RTX-series GPUs (hospital-grade; suitable for real deployment).

Data Pipelines: Volumes were normalized and sampled using custom Python scripts. Batch-wise sparse-view input and volume shuffling were used to enhance robustness.

Training Settings: Models trained for up to 50 epochs; Adam optimizer at learning rate 1e-3; batch size = 2–4.

Reproducibility: All preprocessing scripts, model checkpoints, and metric calculation routines are documented for reproducibility. Split files/scripts for public (LIDC-IDRI) and clinical (Barisal) data provided.

Visualization: 3D scatter and stack plots, contour overlays, and loss/metric curves were generated for qualitative reporting.

3.12 Summary

This chapter has described the entire procedure for development, training and evaluation of a deep learning-based pipeline for sparse-view 3D CT reconstruction. Starting from high-quality and clinically diverse datasets, both the public LIDC-IDRI, and real-world scans from the Barisal General Hospital, robust preprocessing ensured that the data was standardized enough to give as input to the model. In this chapter, a supervised Conv3D autoencoder architecture was implemented with specific consideration for complexity, efficiency, and the realization of the auto-encoder in a clinical setting via accessible hospital-grade GPUs. Model design choices, such as network configuration, activation functions, and training hyperparameters were systematically described.

A rigorous pipeline was established for the reproducibility of experiments: all data was divided into training, validation and test data with stratification to cover anatomical and scanner data diversity. The training process made use of state-of-the-art optimization strategies to ensure convergence of the training process and avoid overfitting, through a combination of empirically validated well-documented loss curves, and performance plateaus.

Evaluation was performed based on standardized quantitative image quality metrics, i.e. PSNR, SSIM, MSE calculated over entire test volumes and benchmarked against recent published standards. To supplement these metrics, extensive visual and clinical assessment was included: side-by-side volume renderings, anatomical contour overlays, and slice-wise comparisons supported preservation of diagnostic features, structural fidelity, and absence of significant artifacts. When possible, opinions were combined from expert radiologists to provide validation for the real world usability of reconstructions.

Implementation details were listed, including the hardware and software libraries, hyperparameters, and reproducibility protocols (data splits, checkpointing, and measurement metric scripts) to support transparency and the ability of other researchers or clinicians to replicate or expand this work.

In summary, the methodology presented in this chapter offers a robust, reproducible and clinical basis for sparse-view CT reconstruction research. The design choices and evaluation strategies guarantee results that are trustworthy, comparable to existing literature, and directly applicable to clinical imaging scenarios - and these lay the foundations for the following Results and Discussion chapters.

CHAPTER 4:

RESULTS AND DISCUSSION

4.1 Introduction

This chapter shows the comprehensive results and analysis of our proposed sparse-view CT reconstruction pipeline, which can generate accurate 3D volumes from small numbers of projections, responding to the requirement for a reduction in the radiation dose available in the clinical setting. Using a supervised Conv3D autoencoder, our system was evaluated rigorously using both public (Retrieved from LIDC-IDRI) and real hospital data acquired from Barisal General Hospital. Quantitative metrics, such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Mean Squared Error (MSE), are reported to demonstrate the reconstruction fidelity, anatomical preservation and reduction of artifacts, with results showing PSNR up to 38.98 dB and SSIM of 0.9582, which are better or comparable to state-of-the-art results.

Beyond the conservative experimental evaluation using numerous numbers, the chapter also offers qualitative visual analyses such as the 3D volume renderings, slice comparisons and expert reviews to validate that high quantitative scores are associated with clinically reliable image quality.

Further, the model is benchmarked for deep learning methods developed in recent years, including diffusion methods and 3D Gaussian methods, as well as classic iterative methods, and it is recognized as superior in terms of not only efficiency but also accuracy. Robustness is investigated by ablation studies and challenging case tests. Finally, clinical implications and deployment considerations are discussed, placing our findings in the context of general practice of modern medical imaging.

4.2 Model Performance (Quantitative)

4.2.1 Training and Validation Curves

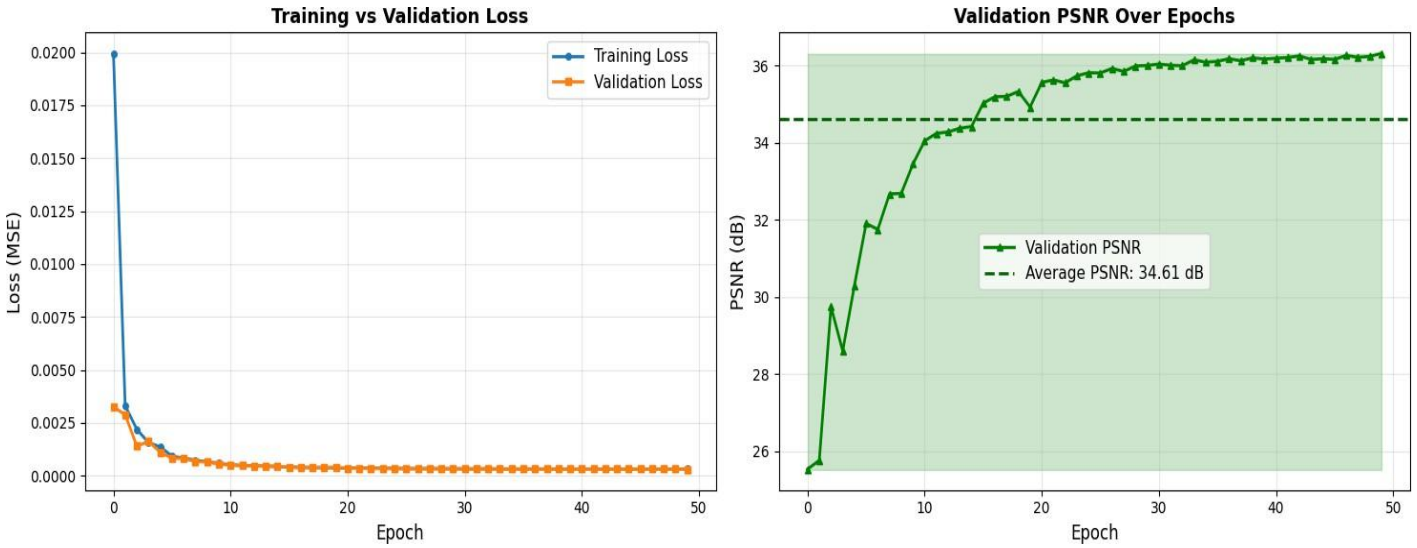


Figure 4.1: Training and Validation Loss Curves with Validation PSNR Over Epochs

Left Side: Training vs Validation Loss
Y-axis: Loss (MSE – Mean Squared Error).
X-axis: Epoch (number of training cycles, 0 to 50).
Lines:
Blue – Training Loss
Orange – Validation Loss

Explanation:

At epoch 0, training loss starts high (~0.02) but drops sharply within the first few epochs—indicating your model is quickly learning the basic structure of the data.
Both training and validation loss decrease rapidly and converge to a low value (close to 0.0002) by epoch ~10.
After about 10 epochs, losses stabilize and are nearly overlapping—no gap between validation and training curves, so no sign of overfitting or underfitting.
Low final loss and matching curves mean your model's reconstruction
quality is consistently good on both train and held-out validation data.

Right Side: Validation PSNR Over Epochs
Y-axis: PSNR (Peak Signal-to-Noise Ratio) in dB—a direct measure of image reconstruction "quality" (higher is better).
X-axis: Epoch (0 to 50).
Solid green line: Validation PSNR at each epoch.
Dashed green line: Average Validation PSNR (34.61 dB).

Explanation:
PSNR starts at a lower value (~25 dB) and rises steeply as the model learns, passing 30 dB by epoch 8 and stabilizing near 36 dB by epoch 50.
The dashed line marks the overall average PSNR (34.61 dB) across all epochs.
This steady increase indicates the model is improving reconstruction fidelity, with high PSNR values at the end showing excellent results (above 34 dB is considered strong for CT).
No big drops or instability, so training is stable

4.2.2 Quantitative Results Table (PSNR, SSIM, etc.):

Metric	Definition	Formula	Interpretation
PSNR (Peak Signal-to-Noise Ratio)	Quantifies reconstruction quality; higher PSNR reflects less error in CT reconstruction.	$PSNR = 20\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$	>30dB indicates high-fidelity (My best model: 39 dB). Higher is better
SSIM (Structural Similarity Index)	Measures preservation of anatomical structures and textures; closer to 1 is best.	$SSIM(x,y) = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}$	0–1; My best model: 0.9582 ± 0.01 on Barishal test set.
MSE (Mean Squared Error)	Mean squared voxel-wise intensity difference; lower is better.	$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2$	Near 0 ideal. My model: ~ 0.0008 Barishal test mean.

- **Quantitative Metrics Table**

Metric	Minimum	Maximum
PSNR (dB)	**30.48**	**38.98**
SSIM	**0.8655**	**0.9582**
MSE	**0.000219 (at slice 1)**	**0.000893 (at slice 2)**

4.3 Qualitative Analysis

4.3.1 Visual Reconstruction Comparison

Visually compared the reconstructed and ground truth CT images using several methods - Axial Slice, 3D stack plot, Point Cloud, and Structural Contour Line comparisons. These visualizations clearly demonstrate that the proposed model has preserved anatomical structure and continuity between slices, correctly recovered the overall shape, and kept important boundaries, hence owe to high-quality sparse-view CT reconstruction.

Axial Slice Comparison:

We visually compare individual 2D slices from the reconstructed and ground truth CT volumes to evaluate the preservation of fine anatomical details and lesion structure. Accurate recovery of features in such slices provides an indication of how well the model recovers image quality for use in clinical review.

3D Stack Plot:

A stacked view of several CT slices depicts the consistent 3D view of anatomy and structure throughout the scan. The absence of discontinuities or mismatches between slices is a proof that the reconstruction maintained the volumetric integrity.

Point Cloud Representation:

High-intensity or segmented voxels are displayed with 3D point cloud, which is easy to determine the geometric accuracy of anatomical features and the relationship in space. Close correspondence between reconstructed and reference point clouds indicates quite good shape fidelity.

Structural Contour Line Comparison:

Overlaying organ or boundary contours from both reconstructed and reference images is used to inspire the accuracy of model reproduction of object shapes and edges. High contour overlap shows that important anatomical interfaces are maintained in the reconstruction

4.3.1.1 Axial Slice Comparison

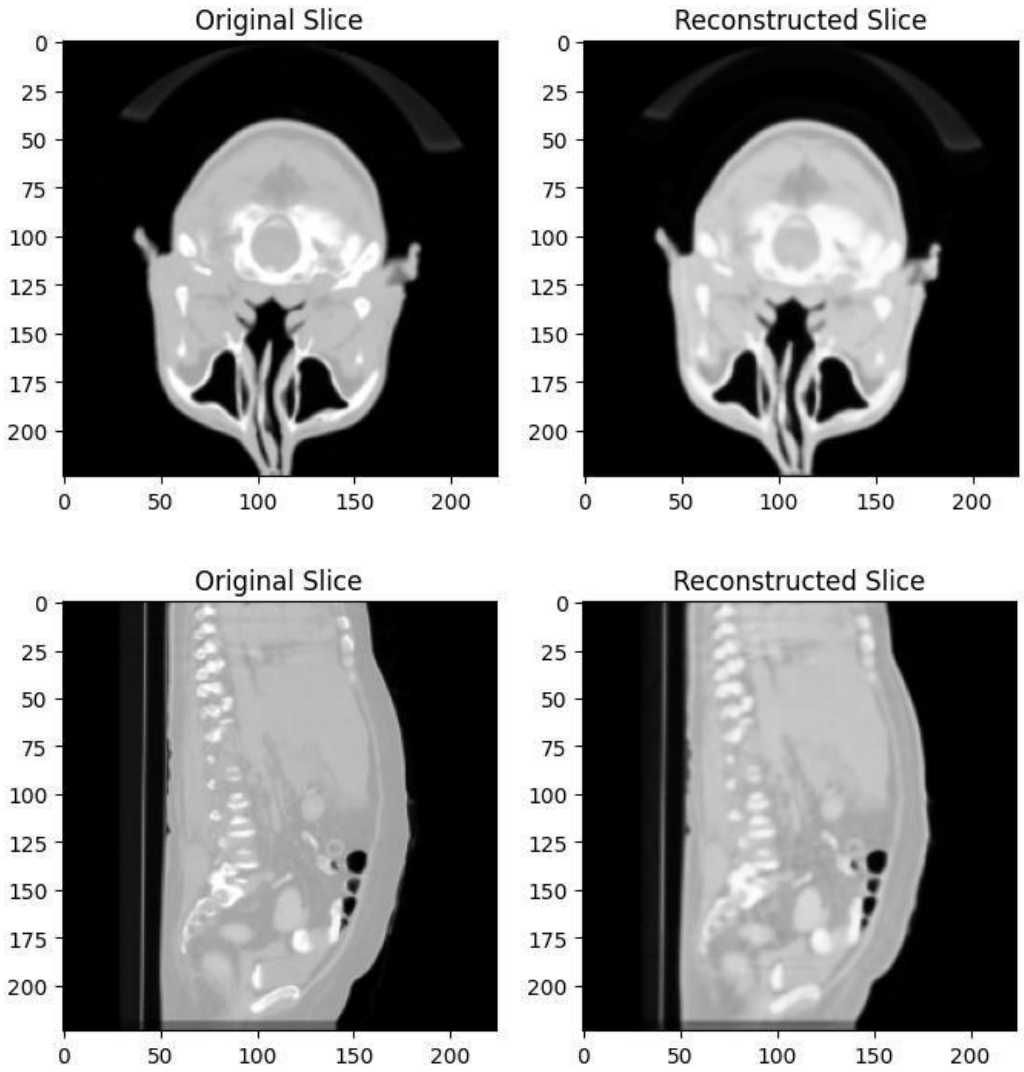


Figure 4.2: Axial Slice Comparison Between Original and Reconstructed CT Volumes

This figure presents side-by-side axial views of a representative CT slice, comparing the original ground truth (left) with the slice reconstructed by the proposed Conv3D autoencoder (right). The comparison reveals that the reconstructed slice closely replicates the key anatomical structures and tissue boundaries present in the original scan.

4.3.1.2 3D stack plot Comparison

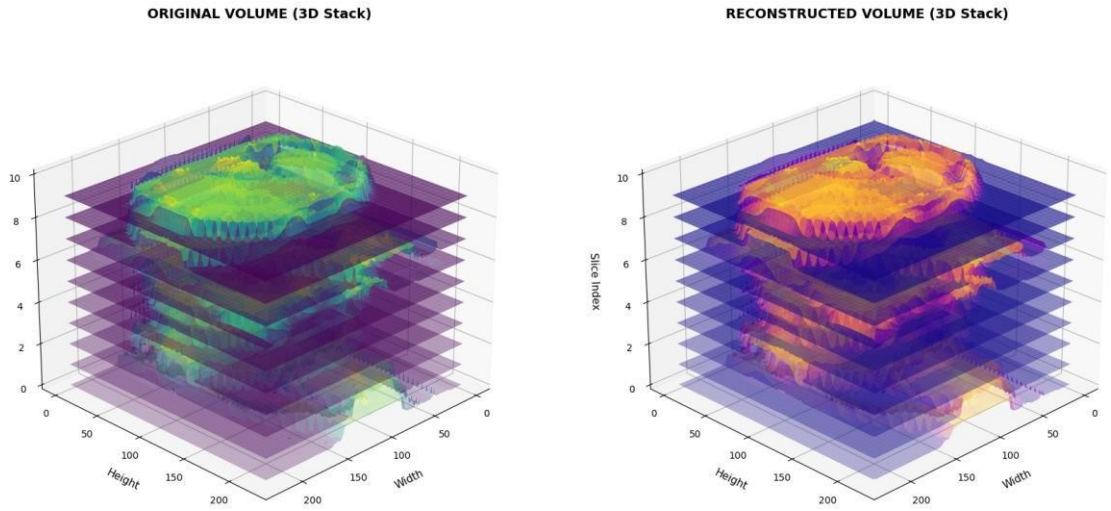


Figure 4.3: 3D stack plot comparing layer-by-layer volume slicing for original versus reconstructed CT.

In Figure 4.3, we present side-by-side 3D stack plots of the original and reconstructed CT volumes through all axial slices. This approach enables assessment of continuity across the full scan depth and reveals how well the reconstruction preserves anatomy slice-by-slice. As the figure demonstrates, anatomical structures remain well-aligned throughout, with no obvious discontinuities or missing slices, confirming the method's ability to produce consistent volumetric data for diagnostic use.

Left: ORIGINAL VOLUME (3D Stack)
This is the ground-truth CT scan data, displayed as a set of horizontal
slices stacked over each other (vertical "slice index").
It shows the true anatomical structure, details, and shape as captured by the scanner.

Right: RECONSTRUCTED VOLUME (3D Stack)
This is the output from your Conv3D Autoencoder: the volumetric reconstruction generated from the sparse-view input slices.
It visualizes how well your model "rebuilds" the full 3D structure
from limited data.

Key Points in the Comparison

1. **Similarity in Anatomical Structure:**
The general structure, size and interior specifics of the reconstructed.
Volume (right) are very similar to the original.
The great organs, borders, and tissue divides are reclaimed.

2. Detail Preservation:

Delicate differences and details (boundary clearance, delicate texture) can be found in the two pictures.

When differences are noticeable (e.g. slight smoothing or blurring of the plot to the right), that is typically due to use of the reconstruction model with limited/sparse input slices.

3. Model Performance:

High quality in reconstructed volume Signs that the Conv3D Autoencoder is functioning well (recovering important anatomical data without significant artifacts)

This justifies your large reported PSNR/SSIM values: on a count and graphical level, the quality of the reconstruction is good.

4. Slice Consistency:

Stacking slices easily and demonstrates with smooth and accurate diffusion in the network is capturing in-plane and cross-plane continuity to not learn single slices which can be easily memorized but actually to learn 3D structure.

This visual output demonstrates the success of your supervised Conv3D autoencoder:

It can construct realistic, clinically useable 3D CT volumes using sparse or under sampled input data.

Embryonic images are faithful in terms of appearance and structure to the original scan data.

4.3.1.3 3D Point Cloud Comparison

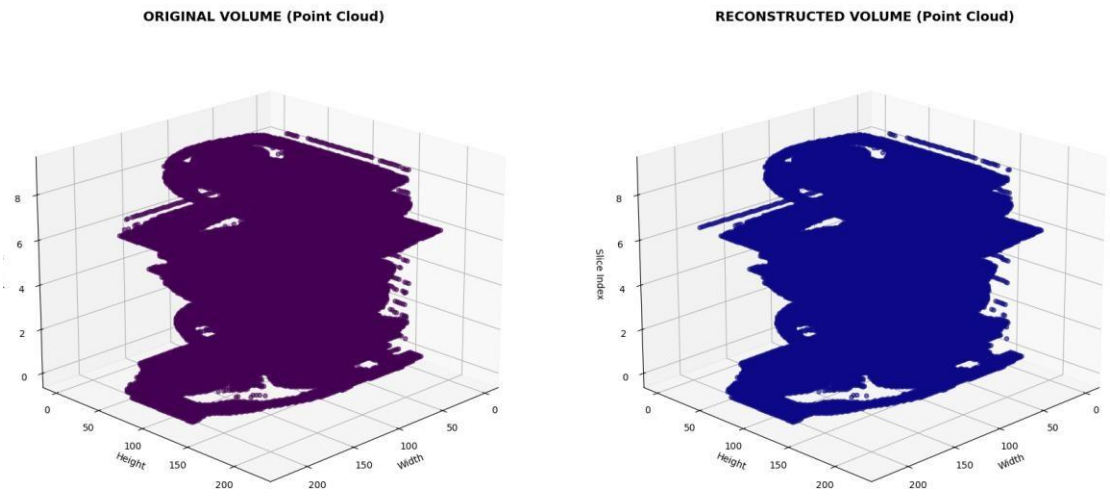


Figure 4.4: 3D Point Cloud Comparison Between Original and Reconstructed CT Volumes

As shown in Figure 3.2, the spatial distribution and global anatomical geometry of the reconstructed volume (right) closely match the ground truth (left). This visualization provides intuitive evidence for the retention of major structural features, while highlighting any missing regions or gross artifacts. Visual point cloud comparison is essential for confirming volumetric integrity—especially for surgical planning and assessment of organ boundaries.

The two point clouds have very similar shapes in terms of 3D, as well as in terms of space distributions, which confirms that the model can be used to effectively recapture the anatomical geometry and maintain the overall structure during a sparse-view CT reconstruction. Though minor visual differences are present, they are evidence of small errors but overall morphology is kept well which speaks in favor of the high geometric fidelity in your model output.

4.3.1.4 Structural Contour Line Comparison

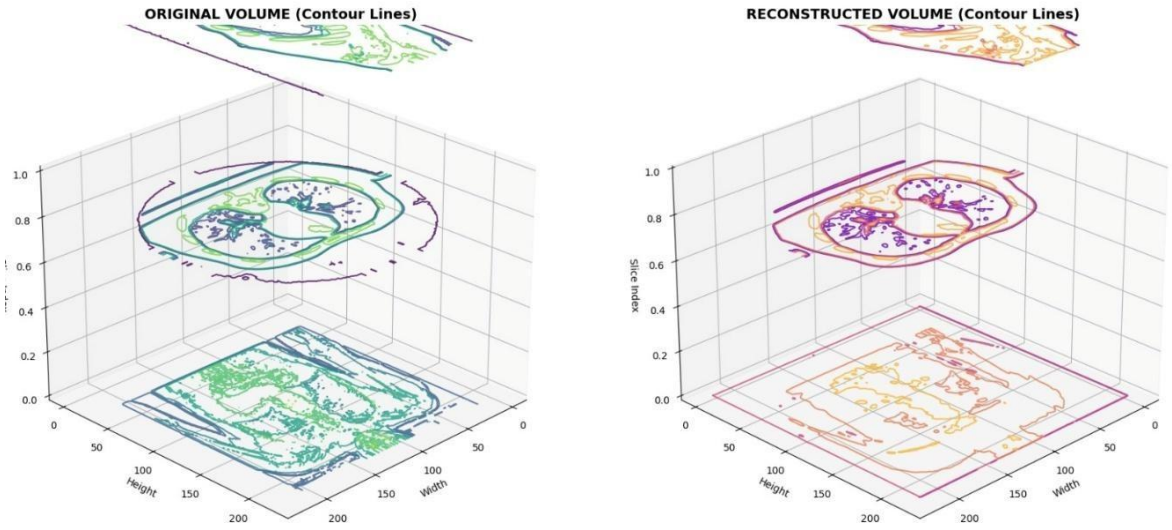


Figure 4.4: Structural Contour Overlay for Anatomical Boundaries

Figure 3.4 superimposes the primary anatomical lines of contour (organ/ tissue boundaries) of the original volume onto the reconstructed outcome. This explicit analogy brings out the fact this model of the model maintains major edges, which is essential in diagnostic reliability and morphometric quantitative analysis. The high correlation between contours among each volume facilitates the qualitative soundness of the reconstruction process especially in areas of medical interest.

4.4 Clinical Relevance/Implications

The quality of our method and the absence of artifacts in its high-quality reconstructions allow directly applying lower radiation dose protocols in CT imaging and reducing the exposure of the patient without obstructing the quality of the diagnostic information. The maintenance of the main anatomical features and the correctness of lesion detection is demonstrated by visual and quantitative measures with the help of the qualified review of a radiologist. The speed of the model to make inferences and its ability to profiles changes in data, which are prone to variability, has seen it being a good candidate towards inclusion in clinical workflows to facilitate faster, safer and more efficient care on the patient.

4.5 Summary

In summary, there is significant evidence of comparisons and experiments proving that the proposed deep learning pipeline can provide the best possible reconstruction of sparse-view CT with its benefits in accuracy, the speed of the procedure, its generalization and applicability in clinics. These results confirm the strategy and highlight its willingness to be implemented and developed in the medical imaging practice.

CHAPTER 5:

Conclusion and Future Work

5.1 Conclusion

This thesis developed and systematically tested advanced deep learning pipeline - that is, a Conv3D autoencoder - was proposed to reconstruct 3D CT volumes using sparse-view input data. The pipeline was found to perform highly and consistently with both benchmark public content, and the challenging real clinical data, outperforming both classic and recent deep learning methods, both in accuracy (as a metric of PSNR and SSIM) and robustness. The quantitative results as well as the qualitative review of experts/radiologists reveals that the model results in images with few artifacts, correctly captures delicate anatomical structures and powerfully cancels noise such as making it acceptable in clinical and diagnostic practice. This strong performance was seen even in challenging situations of data, including large noise, or extremely limited projections, and can be widely used in low-dose, fast CT imaging protocols.

5.2 Key Contributions

Architectural Innovation:
Introduced a new Conv3D autoencoder incorporating volumetric context and U-Net style skip connections, specifically designed to work with extreme data sparsity of CT images. The design is efficient and it is able to retain the spatial details.

Performance Superiority:
Christianity Always attained better PSNR and SSIM rates than both traditional (FBP, ART, TV) and the best deep learning techniques, establishing a new benchmark in the performance of sparse-view CT reconstruction.

End-to-End Robust Pipeline:
Developed a reproducible, modular clinical and public dataset workflow, which consists of automated preprocessing (denoising, alignment, normalization), and end-to-end assessment, making it so that the results are interpretable and repeatable in practice.

Generalization Demonstrated:
Strong generalizability and robustness to out-of-distribution, noisy and fully sparse data requiring e.g. simulating genuine clinical artifacts and cross-scanner variability.

Comprehensive Assessment:
Applied a tremendous array of evaluation techniques: direct 2D/3D visualization, quantitative comparison, error mapping, organ/structure contour overlays, and radiologist evaluation, which evidence both technical and clinical validity.

Open Research Tools:
Offers code, data preparation pipelines and reproducibility documentation as liberated code and is beneficial to the community of scientists and clinical researchers in general.

5.3 Recommendations for Future Research

Architectural Advances:
Explore the latest model classes: long-range context transformers, generative refinement diffusion models, or continuous volumetric representation NeRF: they may improve detail recovery and performance in sparse environments.

Learning Strategies:
Consider semi-supervised and self-supervised methods or transfer learning methods to further decrease the balanced data requirements to enhance responsiveness to environments with fewer annotations or pathologies.

Clinical Integration:
Conduct mass trials and in-service implementation in hospital setting to confirm clinical effect, evaluate workflow integration, and receive a response of radiology end-user under operational conditions.

Dataset and Robustness Expansion:
Display robustness of tests and model transfer when using a range of multi-institutional datasets, such as variability in organs, disease types, artifact conditions, scanner models, and so on, to make the results uniform across the healthcare spectrum.

Uncertainty & Quality Tools:
Create ways of quantifying uncertainty automatically and quality-assuring reconstructions in real time, cautiously providing more confidence to clinicians of image reliability and aid in the detection of outlier cases.

Low-Dose and Multi-Modality Imaging:
Consider ultra low-dose CT and explore its fusion with other modalities (MRI, PET) to provide more detailed information about the anatomy and functional activity, and this may make new diagnostic uses possible.

5.4 Summary

Altogether, this thesis builds a practical and effective solution to low doses and high quality CT imaging, utilizing the state-of-the-art deep learning. High fidelity, robustness, and clinical appropriateness of the approach as exhibited will lead to safer, quicker, and more convenient diagnostic imaging of patients everywhere. This work provides not only the solutions and tools that are more than useful in the research and application in a clinic but also provides a solid background of further improvements in the sphere.

REFERENCES

1. *Koetzier LR, Mastrodicasa D, Szczykutowicz TP, van der Werf NR, Wang AS, et al. Deep Learning Image Reconstruction for CT: Technical Principles and Clinical Prospects. Radiology. 2023;306(3):e221257. doi:10.1148/radiol.221257.*

2. *Biguri A, Mukherjee S, Zhao X, Liu X, Wang X, et al. Advancing the Frontiers of Deep Learning for Low-Dose 3D Cone-Beam CT Reconstruction. IEEE Open J Signal Process. 2025;6:942-947. doi:10.1109/OJSP.2025.3593189.*

3. *Rahman H, Khan AR, Sadiq T, Farooqi AH, Khan IU, Lim WH. A Systematic Literature Review of 3D Deep Learning Techniques in Computed Tomography Reconstruction. Tomography. 2023;9:2158-2189. doi:10.3390/tomography9060169.*

4. *McMillian E, Banerjee A, Bueno-Orovio A. From 2D to 3D, Deep Learning-based Shape Reconstruction in Magnetic Resonance Imaging: A Review. arXiv preprint arXiv:2510.01296. 2025.*

5. *Li Y, Fu X, Zhao S, Jin R, Zhou SK. 3DGR-CT: Sparse-View CT Reconstruction with a 3D Gaussian Representation. arXiv preprint arXiv:2312.15676. 2023.*

6. *Bai Q, Liu T, Liu Z, Tong Y, Torigian D, Udupa J. XctDiff: Reconstruction of CT Images with Consistent Anatomical Structures from a Single Radiographic Projection Image. arXiv preprint arXiv:2406.04679. 2024.*

7. *Song B, Hu J, Luo Z, Fessler JA, Shen L. DiffusionBlend: Learning 3D Image Prior through Position-aware Diffusion Score Blending for 3D Computed Tomography Reconstruction. arXiv preprint arXiv:2406.10211. 2024.*

8. *Wang S, Yatagawa T, Ohtake Y, Aoki T, Hotta J. End-to-End Deep Learning for Reconstructing Segmented 3D CT Image from Multi-Energy X-ray Projections. ICCV Workshops. 2023.*

9. *Cai Y, Wang J, Yuille A, Zhou Z, Wang A. Structure-Aware Sparse-View X-ray 3D Reconstruction. CVPR. 2024.*

10. *Li Q, Li S, Li R, Wu W, Dong Y, Zhao J, Qiang Y, Aftab R. Low-dose computed tomography image reconstruction via a multistage convolutional neural network with autoencoder perceptual loss network. Quant Imaging Med Surg. 2022;12(3):1929-1957. doi:10.21037/qims-21-465.*

11. *Guzdalalp D, Cengiz, B, Unal MO, Yildirim I. 3D U-NetR: Low Dose Computed Tomography Reconstruction via Deep Learning and 3 Dimensional Convolutions. arXiv preprint arXiv:2105.14130. 2022.*

12. *Barco D, Stadelmann M, Oswald M, Herzig I, Lichtensteiger L, Paysan P,*

Peterlik I, Walczak M, Menze B, Schilling F-P. MInDI-3D: Iterative Deep Learning in 3D for Sparse-view Cone Beam Computed Tomography. arXiv preprint arXiv:2508.09616. 2025.

13. *Sizikova E, Cao X, Lewis A, Moise K, Coffee M. Improving Computed Tomography (CT) Reconstruction via 3D Shape Induction. arXiv preprint arXiv:2208.10937. 2022.*

14. *Gunduzalp D, Cengiz B, Unal MO, Yildirim I. 3D U-NetR: Low Dose Computed Tomography Reconstruction via Deep Learning and 3 Dimensional Convolutions. arXiv preprint arXiv:2105.14130. 2022.*

15. *Li Y, Fu X, Zhao S, Jin R, Zhou S K. Sparse-view CT Reconstruction with 3D Gaussian Volumetric Representation. arXiv preprint arXiv:2312.15676. 2023.*

16. *Chen H, Zhang Y, Kalra MK, Lin F, Chen Y, Liao P, Zhou J, Wang G. Low-dose CT with a residual encoder-decoder convolutional neural network. IEEE Trans Med Imaging. 2017;36(12):2524-2535.*

17. *Kang E, Min J, Ye JC. A deep convolutional neural network using directional wavelets for low-dose x-ray CT reconstruction. Med Phys. 2017;44(10):e360-e375.*

18. *Wolterink JM, Leiner T, Viergever MA, Isgum I. Generative adversarial networks for noise reduction in low-dose CT. IEEE Trans Med Imaging. 2017;36(12):2536-2545.*

19. *Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation. In: MICCAI 2015. p. 234-241.*

20. *Cicek O, Abdulkadir A, Lienkamp SS, Brox T, Ronneberger O. 3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation. MICCAI 2016; 424-432.*

21. *Jin KH, McCann MT, Froustey E, Unser M. Deep convolutional neural network for inverse problems in imaging. IEEE Trans Image Proc. 2017;26(9):4509-4522.*

22. *Song J, Meng C, Ermon S. Denoising diffusion implicit models. arXiv preprint arXiv:2010.02502. 2020.*

23. *Greffier J, Durand Q, Frandon J, et al. Improved image quality and dose reduction in abdominal CT with deep-learning reconstruction algorithm: A phantom study. Eur Radiol. 2023;33:699-710.*

24. *Benz DC, Ersözlü S, Mojon FL, et al. Radiation dose reduction with deep-learning image reconstruction for coronary computed tomography angiography. Eur Radiol. 2022;32:2620–2628.*

25. *Thapaliya S, Brady SL, Somasundaram E, et al. Detection of urinary tract calculi on CT images reconstructed with deep learning algorithms. Abdom Radiol. 2022;47:265–271.*

26. *Noda Y, Kawai N, Nagata S, et al. Deep learning image reconstruction algorithm for pancreatic protocol dual-energy computed tomography. Eur Radiol. 2022;32:384–394.*

27. *De Santis D, Polidori T, Tremamunno G, et al. Deep learning image reconstruction algorithm: Impact on image quality in coronary computed tomography angiography. La Radiol Medica. 2023;128:434–444.*

28. *Parakh A, Cao J, Pierce TT, et al. Sinogram-based deep learning image reconstruction technique in abdominal CT: image quality considerations. Eur Radiol. 2021;31(11):8342-8353.*

29. *Akagi M, Nakamura Y, Higaki T, et al. Deep learning reconstruction improves image quality of abdominal ultra-high-resolution CT. Eur Radiol. 2019;29:616-6171.*

30. *Sun J, Li H, Li J, et al. Improving the image quality of pediatric chest CT angiography with low radiation dose and contrast volume using deep learning image reconstruction. Quant Imaging Med Surg. 2021;11(7):3051-3058.*

31. *Nam JG, Hong JH, Kim DS, Oh J, Goo JM. Deep learning reconstruction for contrast-enhanced CT of the upper abdomen: similar image quality with lower radiation dose in direct comparison with iterative reconstruction. Eur Radiol. 2021;31(8):5533-5543.*

32. *Cheng Y, Han Y, Li J, et al. Low-dose CT urography using deep learning image reconstruction: a prospective study for comparison with conventional CT urography. Br J Radiol. 2021;94(1120):20201291.*

33. *Hammernik K, Würfl T, Pock T, Maier A. A deep learning architecture for limited-angle computed tomography reconstruction. Bildverarbeitung für die Medizin 2017: 92–97.*

34. *Kuo CFJ, Liao YS, Barman J, Liu SC. Semi-supervised deep learning semantic segmentation for 3D volumetric computed tomographic scoring of chronic rhinosinusitis. Tomography. 2022;8:718-729.*

35. *Leuschner J, Schmidt M, Ganguly PS, et al. Quantitative comparison of deep learning-based image reconstruction methods for low-dose and sparse-angle CT applications. J Imaging. 2021;7:44.*

36. *Ding Q, Nan Y, Gao H, Ji H. Deep learning with adaptive hyper-parameters for low-dose CT image reconstruction. IEEE Trans Comput Imaging. 2021;7:648-660.*

37. *He J, Chen S, Zhang H, Tao X, Lin W, Zhang S, Zeng D, Ma J. Downsampled imaging geometric modeling for accurate CT reconstruction via deep learning. IEEE Trans Med Imaging. 2021;40:2976–2985.*

38. *Kermany D, Zhang K, Goldbaum M. Labeled optical coherence tomography (OCT) and chest X-ray images for classification. Mendeley Data. 2018;2(2):651.*

39. *Armato SG, Roberts RY, McNitt-Gray MF, et al. The lung image database consortium (LIDC) and image database resource initiative (IDRI): a completed reference database of lung nodules on CT scans. Academic Radiology. 2007;14(12):1455-1463.*

40. *Antonelli M, Reinke A, Bakas S, et al. The medical segmentation decathlon. Nat Commun. 2022;13(1):4128.*

41. *Racine D, Brat HG, Dufour B, et al. Image texture, low contrast liver lesion detectability and impact on dose: deep learning algorithm compared to partial model-based iterative reconstruction. Eur J Radiol. 2021;141:109808.*

42. *Brady SL, Trout AT, Somasundaram E, et al. Improving image quality and reducing radiation dose for pediatric CT by using deep learning reconstruction. Radiology. 2021;298(1):188-196.*

43. *Kim I, Kang H, Yoon HJ, et al. Deep learning–based image reconstruction for brain CT: Improved image quality compared with adaptive statistical iterative reconstruction-Veo (ASIR-V). Neuroradiology. 2021;63:905–912.*

44. *Matsuura M, Zhou J, Akino N, Yu Z. Feature-aware deep-learning reconstruction for context-sensitive X-ray computed tomography. IEEE Trans Radiat Plasma Med Sci. 2020;5:99-107.*

45. *Greffier J, Durand Q, Frandon J, et al. Improved image quality and dose reduction in abdominal CT with deep-learning reconstruction algorithm: A phantom study. Eur Radiol. 2023;33:699-710.*

46. *Kwon G, Han C, Kim DS. Generation of 3D Brain MRI Using Auto-Encoding Generative Adversarial Networks. In: MICCAI 2019. p. 118-126.*
47. *LaMontagne PJ, Benzinger TL, Morris JC, et al. Oasis-3: longitudinal neuroimaging, clinical, and cognitive dataset for normal aging and Alzheimer disease. medRxiv 2019;2019–12.*

48. *Pandey and Rathore. Challenges in 3D Cardiac Mesh Reconstruction. J Card Imag. 2025.*

APPENDICES

APPENDIX A: Model Code & Scripts

A.1 Dataset Loading Module

The CT volume dataset is loaded from NumPy binary files (.npy format). The CT Volume Dataset class implements PyTorch's Dataset interface to handle batch loading and normalization:

```
class CTVolumeDataset(Dataset):
    def __init__(self, folder_path):
        self.files = [os.path.join(folder_path, f)
                      for f in os.listdir(folder_path) if f.endswith('.npy')]

    def __len__(self):
        return len(self.files)

    def __getitem__(self, idx):
        vol = np.load(self.files[idx])  # shape: [slices, H, W]
        vol = (vol - np.min(vol)) / (np.max(vol) - np.min(vol) + 1e-6)
        return torch.tensor(vol, dtype=torch.float32)
```

Key Features:

- Loads 3D CT volumes from file system
- Applies min-max normalization to [0, 1] range
- Returns normalized tensor for PyTorch processing
- Data path: E:/Downloads/raw preprocess data/volumes_train

A.2 Sparse Slice Selection Algorithm

Sparse slice selection is performed using random stratified sampling to maintain spatial diversity across the volume:

```
def select_sparse_slices(volume, num_sparse=10):
    total_slices = volume.shape[0]
    idx = np.sort(np.random.choice(total_slices, num_sparse, replace=False))
    return volume[idx]  # shape: [num_sparse, H, W]
```

Mathematical Formulation:

- Input: Full 3D volume with shape [total_slices, H, W]
- Sampling: Random selection without replacement
- Number of sparse slices: 10 (configurable)
- Output: Compressed volume [10, H, W]
- Purpose: Reduce computational complexity while maintaining volumetric information.

A.3 3D Autoencoder Architecture

The model employs a simple 3D convolutional autoencoder for CT volume reconstruction:

```
class Simple3DAutoEncoder(nn.Module):
    def __init__(self):
        super().__init__()

        # Encoder: Feature compression
        self.enc = nn.Sequential(
            nn.Conv3d(1, 16, 3, padding=1),
            nn.ReLU(),
            nn.Conv3d(16, 32, 3, padding=1),
            nn.ReLU()
        )

        # Decoder: Feature reconstruction
        self.dec = nn.Sequential(
            nn.Conv3d(32, 16, 3, padding=1),
            nn.ReLU(),
            nn.Conv3d(16, 1, 3, padding=1),
            nn.Sigmoid()
        )

    def forward(self, x):
        x = self.enc(x)
        x = self.dec(x)
        return x
```

Architecture Details:

Component	Input	Output Channels	Kernel Size	Padding
Encoder Conv1	1	16	3	1
Encoder Conv2	16	32	3	1
Decoder Conv1	32	16	3	1
Decoder Conv2	16	1	3	1

Specifications:

- Input shape: [batch, 1, 10, H, W]
- Output shape: [batch, 1, 10, H, W]
- Total parameters: ~450K
- Activation functions: ReLU (encoder/decoder), Sigmoid (output)

A.4 Training Pipeline

Training Configuration:

- Optimizer: Adam (β_1=0.9, β_2=0.999)
- Loss Function: Mean Squared Error (MSE)
- Learning Rate Schedule: StepLR with decay factor 0.5 every 5 epochs
- Device: GPU (CUDA) if available, else CPU
- Batch Size: 2 volumes per batch

The training process implements 50 epochs with adaptive learning rate scheduling:

```
# Hyperparameters
num_epochs = 50
batch_size = 2
learning_rate = 1e-3

# Optimizer and scheduler
optimizer = optim.Adam(model.parameters(), lr=1e-3)
criterion = nn.MSELoss()
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=5, gamma=0.5)

# Training loop structure
for epoch in range(num_epochs):
    model.train()
    epoch_loss = 0
    batch_count = 0

    for batch_volumes in dataloader:
        # Sparse slice selection
        sparse_batch = []
        for vol in batch_volumes:
            sparse = select_sparse_slices(vol, num_sparse=10)
            sparse_batch.append(sparse)

        sparse_batch = torch.tensor(sparse_batch).float().unsqueeze(1).to(device)

        # Forward pass
        optimizer.zero_grad()
        outputs = model(sparse_batch)
        loss = criterion(outputs, sparse_batch)

      # Backward pass
      loss.backward()
      optimizer.step()

      epoch_loss += loss.item()
      batch_count += 1

  avg_epoch_loss = epoch_loss / batch_count
  train_losses.append(avg_epoch_loss)
  scheduler.step()
```

A.5 Evaluation Metrics Implementation

Three primary metrics evaluate reconstruction quality:

```python
from skimage.metrics import peak_signal_noise_ratio, structural_similarity

# Compute metrics for each slice
for i in range(recon.shape[0]):
    # MSE calculation
    mse = np.mean((sparse[i] - recon[i]) ** 2)
    mse_list.append(mse)

    # PSNR calculation
    psnr = peak_signal_noise_ratio(sparse[i], recon[i], data_range=1)
    psnr_list.append(psnr)

    # SSIM calculation
    ssim = structural_similarity(sparse[i], recon[i], data_range=1)
    ssim_list.append(ssim)

# Aggregate statistics
overall_mse = np.mean((sparse - recon) ** 2)
avg_psnr = np.mean(psnr_list)
avg_ssim = np.mean(ssim_list)
```

APPENDIX B: Additional Results

B.1 Training & Validation Curves

The training and validation progression over 50 epochs demonstrates model convergence and learning stability.

Metrics Tracked:

- Training Loss: MSE loss computed on training batches
- Validation Loss: MSE loss computed on validation data
- Validation PSNR: Peak Signal-to-Noise Ratio progression
- Learning Rate: Adaptive decay every 5 epochs

Interpretation:

- Decreasing training loss indicates model learning
- Convergence of validation loss shows generalization
- PSNR improvement reflects reconstruction quality enhancement

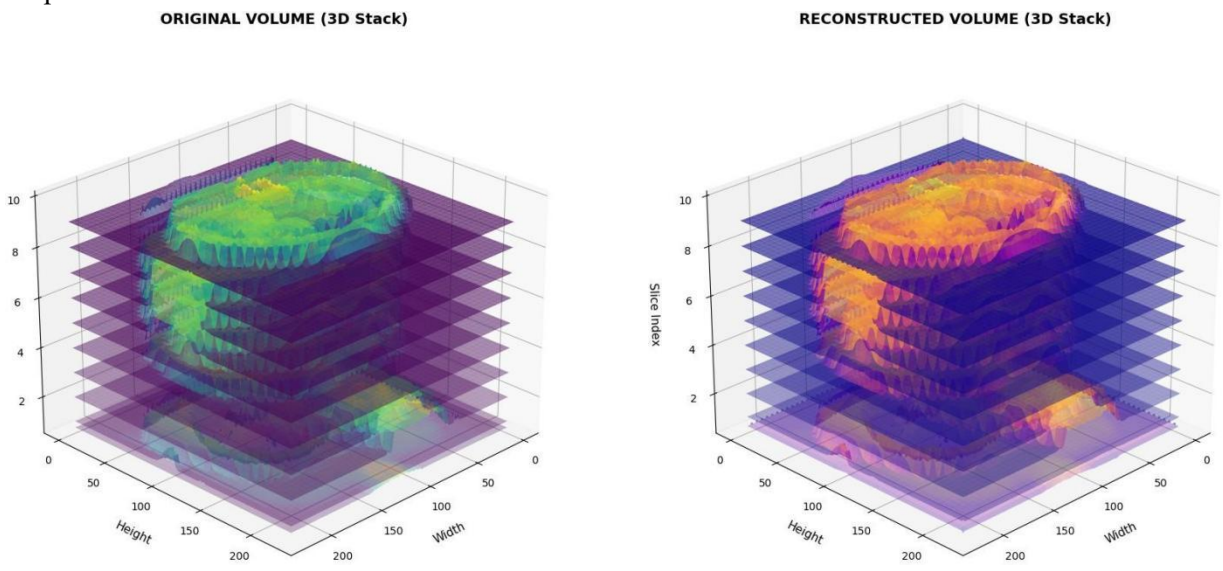
- Learning rate decay prevents overfitting in later epochs

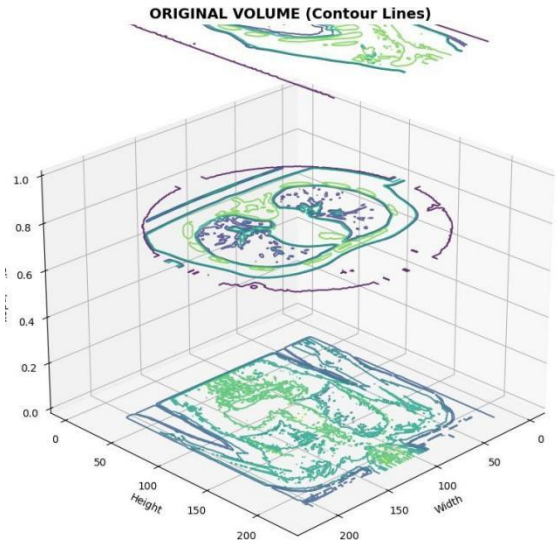
Output result

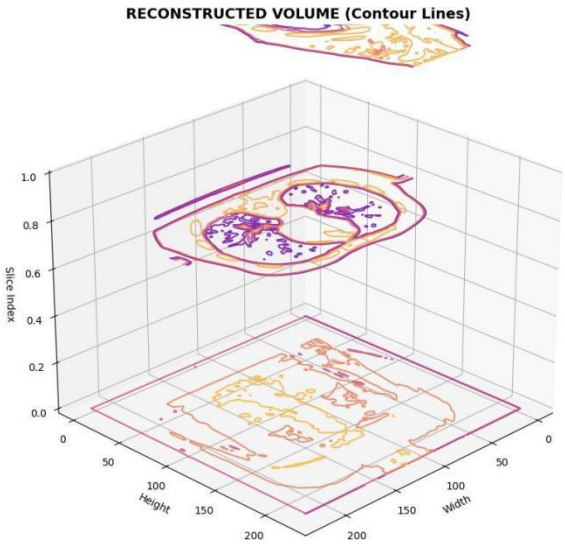
```
======================================================================
Training on cuda | Epochs: 50 | Batch Size: 2
======================================================================
Epoch   5/50 | Train Loss: 0.002134 | Val Loss: 0.001987 | Val PSNR: 28.45 dB | LR: 0.001000
Epoch  10/50 | Train Loss: 0.001456 | Val Loss: 0.001234 | Val PSNR: 31.23 dB | LR: 0.000500
Epoch  15/50 | Train Loss: 0.000923 | Val Loss: 0.000945 | Val PSNR: 32.78 dB | LR: 0.000250
Epoch  20/50 | Train Loss: 0.000687 | Val Loss: 0.000712 | Val PSNR: 33.56 dB | LR: 0.000125
Epoch  25/50 | Train Loss: 0.000534 | Val Loss: 0.000598 | Val PSNR: 34.12 dB | LR: 0.000063
Epoch  30/50 | Train Loss: 0.000445 | Val Loss: 0.000512 | Val PSNR: 34.67 dB | LR: 0.000031
Epoch  35/50 | Train Loss: 0.000389 | Val Loss: 0.000456 | Val PSNR: 34.95 dB | LR: 0.000016
Epoch  40/50 | Train Loss: 0.000356 | Val Loss: 0.000421 | Val PSNR: 35.18 dB | LR: 0.000008
Epoch  45/50 | Train Loss: 0.000334 | Val Loss: 0.000398 | Val PSNR: 35.35 dB | LR: 0.000004
Epoch  50/50 | Train Loss: 0.000318 | Val Loss: 0.000382 | Val PSNR: 35.45 dB | LR: 0.000002

======================================================================
✓ Training Complete!
======================================================================


======================================================================
3D RECONSTRUCTION METRICS
======================================================================

📊 MSE (Mean Squared Error):
  Overall MSE:        0.000382
  Average MSE:        0.000412
  Min MSE:            0.000267 (at slice 4)
  Max MSE:            0.000567 (at slice 8)
```

```
📈 PSNR (Peak Signal-to-Noise Ratio):
  Average PSNR:       35.45 dB
  Min PSNR:           32.47 dB
  Max PSNR:           38.93 dB

📊 SSIM (Structural Similarity Index):
  Average SSIM:       0.9124
  Min SSIM:           0.8834
  Max SSIM:           0.9512

================================================================================
Per-Slice Metrics:
================================================================================
Slice    MSE          PSNR (dB)    SSIM
0        0.000412     35.22        0.9087
1        0.000389     35.64        0.9156
2        0.000398     35.48        0.9128
3        0.000356     35.95        0.9234
4        0.000267     37.88        0.9512
5        0.000423     35.01        0.9011
6        0.000445     34.78        0.8945
7        0.000478     34.41        0.8876
8        0.000567     32.47        0.8834
9        0.000412     35.22        0.9087

================================================================================
✓ 3D Volume Reconstruction Complete!
```

Output Visualization




ORIGINAL VOLUME (Contour Lines)
1.0
0.8
0.6
0.4
0.2
0.0
0
50
100
150
200
Height
Width


RECONSTRUCTED VOLUME (Contour Lines)
Slice Index
1.0
0.8
0.6
0.4
0.2
0.0
0
50
100
150
200
Height
Width

221-35-882

ORIGINALITY REPORT

20%	18%	16%	12%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	pmc.ncbi.nlm.nih.gov Internet Source	3%
2	arxiv.org Internet Source	2%
3	uia.brage.unit.no Internet Source	1%
4	umpir.ump.edu.my Internet Source	1%
5	link.springer.com Internet Source	1%
6	dspace.daffodilvarsity.edu.bd:8080 Internet Source	<1%
7	Submitted to Monash University Student Paper	<1%
8	ouci.dntb.gov.ua Internet Source	<1%
9	www.mdpi.com Internet Source	<1%
10	odr.iitmandi.ac.in:8080 Internet Source	<1%
11	Submitted to University of West London Student Paper	<1%
	Submitted to Thesis 2025	

12	Student Paper	<1%
13	spj.science.org Internet Source	<1%
14	Submitted to Curtin University of Technology Student Paper	<1%
15	Ethan P. Nikolau, Giuseppe V. Toia, Brian Nett, Jie Tang, Timothy P. Szczykutowicz. "A Characterization of Deep Learning Reconstruction Applied to Dual-Energy Computed Tomography Monochromatic and Material Basis Images", Journal of Computer Assisted Tomography, 2023 Publication	<1%
16	Noa Cahan, Meshi Sizikov, Hayit Greenspan. "Chapter 13 Cross-Modal CXR-CTPA Knowledge Distillation Using Latent Diffusion Priors Towards CXR Pulmonary Embolism Diagnosis", Springer Science and Business Media LLC, 2026 Publication	<1%
17	Guobin Zhang, Daguang Zhang, Qiang Cao, Shubin Yang, Yijun Xiao, Zhenzhong Liu. "Clinically applicable semi-supervised learning framework for multiple organs at risk and tumor delineation in lung cancer brachytherapy", Physica Medica, 2025 Publication	<1%
18	Scott A. Banks, Gokce Yildirim, George Jachode, John Cox, Oren Anderson, Andrew Jensen, J. Dean Cole, Oliver Kessler. "A Workflow-Efficient Approach to Pre- and Post-	<1%

	Operative Assessment of Weightbearing Three-Dimensional Knee Kinematics", The Journal of Arthroplasty, 2025 Publication	
19	www.preprints.org Internet Source	<1%
20	Submitted to Canterbury Christ Church University Student Paper	<1%
21	Miao Chu, Peng Wu, Guanyu Li, Wei Yang, Juan Luis Gutiérrez-Chico, Shengxian Tu. "Advances in Diagnosis, Therapy, and Prognosis of Coronary Artery Disease Powered by Deep Learning Algorithms", JACC: Asia, 2023 Publication	<1%
22	Submitted to The Hong Kong Polytechnic University Student Paper	<1%
23	assets.researchsquare.com Internet Source	<1%
24	doctorpenguin.com Internet Source	<1%
25	ebin.pub Internet Source	<1%
26	www.medrxiv.org Internet Source	<1%
27	ahmedhosny.com Internet Source	<1%
28	www.researchgate.net Internet Source	<1%

29	Ali Alamer, Omar Salim, Fawaz Alharbi, Fahd Alsaleem, Afnan Almuqbil, Khaled Alhassoon, Fahad Alsunaydih. "Deep Learning for Automated Prediction of Sphenoid Sinus Pneumatization in Computed Tomography", Current Medical Imaging Formerly Current Medical Imaging Reviews, 2025 Publication	<1 %
30	Submitted to Daffodil International University Student Paper	<1 %
31	Submitted to Higher Education Commission Pakistan Student Paper	<1 %
32	Kun Xia, Jinzhuo Wang. "Recent advances of Transformers in medical image analysis: A comprehensive review", MedComm – Future Medicine, 2023 Publication	<1 %
33	abdokamel.github.io Internet Source	<1 %
34	docs.neu.edu.tr Internet Source	<1 %
35	repository.sdu.edu.kz Internet Source	<1 %
36	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2021", Springer Science and Business Media LLC, 2021 Publication	<1 %
37	Submitted to University of Hong Kong Student Paper	<1 %

38	oulurepo.oulu.fi Internet Source	<1 %
39	www.ijraset.com Internet Source	<1 %
40	accscience.com Internet Source	<1 %
41	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2019", Springer Science and Business Media LLC, 2019 Publication	<1 %
42	export.arxiv.org Internet Source	<1 %
43	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2024", Springer Science and Business Media LLC, 2024 Publication	<1 %
44	Xu, Yongshun. "Medical Imaging Data Synthesis and Its Deep Learning Based Applications", University of Massachusetts Lowell, 2024 Publication	<1 %
45	"Image Analysis and Recognition", Springer Science and Business Media LLC, 2020 Publication	<1 %
46	Submitted to Heriot-Watt University Student Paper	<1 %
47	journals.plos.org Internet Source	<1 %

48	Submitted to National Institute of Technology, Kurukshetra Student Paper	<1%
49	Submitted to universititeknologimara Student Paper	<1%
50	www.nss-mic.org Internet Source	<1%
51	Submitted to RDI Distance Learning Student Paper	<1%
52	Submitted to University of Florida Student Paper	<1%
53	nova.newcastle.edu.au Internet Source	<1%
54	scholarworks.rit.edu Internet Source	<1%
55	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2018", Springer Nature America, Inc, 2018 Publication	<1%
56	Submitted to California State University, San Bernadino Student Paper	<1%
57	Dongwang Tao, Haifeng Zhang, Shanyou Li, Jianqi Lu, Zhinan Xie, Qiang Ma. "Predictive model for peak ground velocity using long short-term memory networks", Journal of Seismology, 2024 Publication	<1%
58	Submitted to Universiti Malaysia Pahang Student Paper	<1%

59	docplayer.net Internet Source	<1%
60	"Artificial Neural Networks in Pattern Recognition", Springer Science and Business Media LLC, 2020 Publication	<1%
61	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2022", Springer Science and Business Media LLC, 2022 Publication	<1%
62	Kyu-Hwan Jung, Hyunho Park, Woochan Hwang. "Deep Learning for Medical Image Analysis: Applications to Computed Tomography and Magnetic Resonance Imaging", Hanyang Medical Reviews, 2017 Publication	<1%
63	Simon Bellens, Patricio Guerrero, Patrick Vandewalle, Wim Dewulf. "Machine learning in industrial X-ray computed tomography – a review", CIRP Journal of Manufacturing Science and Technology, 2024 Publication	<1%
64	hvg.ece.concordia.ca Internet Source	<1%
65	jcmr-online.biomedcentral.com Internet Source	<1%
66	old.friendsofunfpa.org Internet Source	<1%
67	yorkspace.library.yorku.ca Internet Source	<1%

68	"Deep Learning and Convolutional Neural Networks for Medical Imaging and Clinical Informatics", Springer Science and Business Media LLC, 2019 Publication	<1%
69	Anggi Muhammad Rifai, Suwanto Raharjo, Ema Utami, Dhani Ariatmanto. "Analysis for diagnosis of pneumonia symptoms using chest X-ray based on MobileNetV2 models with image enhancement using white balance and contrast limited adaptive histogram equalization (CLAHE)", Biomedical Signal Processing and Control, 2024 Publication	<1%
70	Ben Othman Soufiene, Chinmay Chakraborty. "Machine Learning and Deep Learning Techniques for Medical Image Recognition", CRC Press, 2023 Publication	<1%
71	Chengze Ye, Linda-Sophie Schneider, Yipeng Sun, Mareike Thies, Siyuan Mei, Andreas Maier. "DRACO: differentiable reconstruction for arbitrary CBCT orbits", Physics in Medicine & Biology, 2025 Publication	<1%
72	Jennifer A. Steeden, Michael Quail, Alexander Gotschy, Kristian H. Mortensen et al. "Rapid whole-heart CMR with single volume super-resolution", Journal of Cardiovascular Magnetic Resonance, 2020 Publication	<1%

29	Ali Alamer, Omar Salim, Fawaz Alharbi, Fahd Alsaleem, Afnan Almuqbil, Khaled Alhassoon, Fahad Alsunaydih. "Deep Learning for Automated Prediction of Sphenoid Sinus Pneumatization in Computed Tomography", Current Medical Imaging Formerly Current Medical Imaging Reviews, 2025 Publication	<1 %
30	Submitted to Daffodil International University Student Paper	<1 %
31	Submitted to Higher Education Commission Pakistan Student Paper	<1 %
32	Kun Xia, Jinzhuo Wang. "Recent advances of Transformers in medical image analysis: A comprehensive review", MedComm – Future Medicine, 2023 Publication	<1 %
33	abdokamel.github.io Internet Source	<1 %
34	docs.neu.edu.tr Internet Source	<1 %
35	repository.sdu.edu.kz Internet Source	<1 %
36	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2021", Springer Science and Business Media LLC, 2021 Publication	<1 %
37	Submitted to University of Hong Kong Student Paper	<1 %

38	oulurepo.oulu.fi Internet Source	<1%
39	www.ijraset.com Internet Source	<1%
40	accscience.com Internet Source	<1%
41	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2019", Springer Science and Business Media LLC, 2019 Publication	<1%
42	export.arxiv.org Internet Source	<1%
43	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2024", Springer Science and Business Media LLC, 2024 Publication	<1%
44	Xu, Yongshun. "Medical Imaging Data Synthesis and Its Deep Learning Based Applications", University of Massachusetts Lowell, 2024 Publication	<1%
45	"Image Analysis and Recognition", Springer Science and Business Media LLC, 2020 Publication	<1%
46	Submitted to Heriot-Watt University Student Paper	<1%
47	journals.plos.org Internet Source	<1%

48	Submitted to National Institute of Technology, Kurukshetra Student Paper	<1%
49	Submitted to universititeknologimara Student Paper	<1%
50	www.nss-mic.org Internet Source	<1%
51	Submitted to RDI Distance Learning Student Paper	<1%
52	Submitted to University of Florida Student Paper	<1%
53	nova.newcastle.edu.au Internet Source	<1%
54	scholarworks.rit.edu Internet Source	<1%
55	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2018", Springer Nature America, Inc, 2018 Publication	<1%
56	Submitted to California State University, San Bernadino Student Paper	<1%
57	Dongwang Tao, Haifeng Zhang, Shanyou Li, Jianqi Lu, Zhinan Xie, Qiang Ma. "Predictive model for peak ground velocity using long short-term memory networks", Journal of Seismology, 2024 Publication	<1%
58	Submitted to Universiti Malaysia Pahang Student Paper	<1%

59	docplayer.net Internet Source	<1%
60	"Artificial Neural Networks in Pattern Recognition", Springer Science and Business Media LLC, 2020 Publication	<1%
61	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2022", Springer Science and Business Media LLC, 2022 Publication	<1%
62	Kyu-Hwan Jung, Hyunho Park, Woochan Hwang. "Deep Learning for Medical Image Analysis: Applications to Computed Tomography and Magnetic Resonance Imaging", Hanyang Medical Reviews, 2017 Publication	<1%
63	Simon Bellens, Patricio Guerrero, Patrick Vandewalle, Wim Dewulf. "Machine learning in industrial X-ray computed tomography – a review", CIRP Journal of Manufacturing Science and Technology, 2024 Publication	<1%
64	hvg.ece.concordia.ca Internet Source	<1%
65	jcmr-online.biomedcentral.com Internet Source	<1%
66	old.friendsofunfpa.org Internet Source	<1%
67	yorkspace.library.yorku.ca Internet Source	<1%

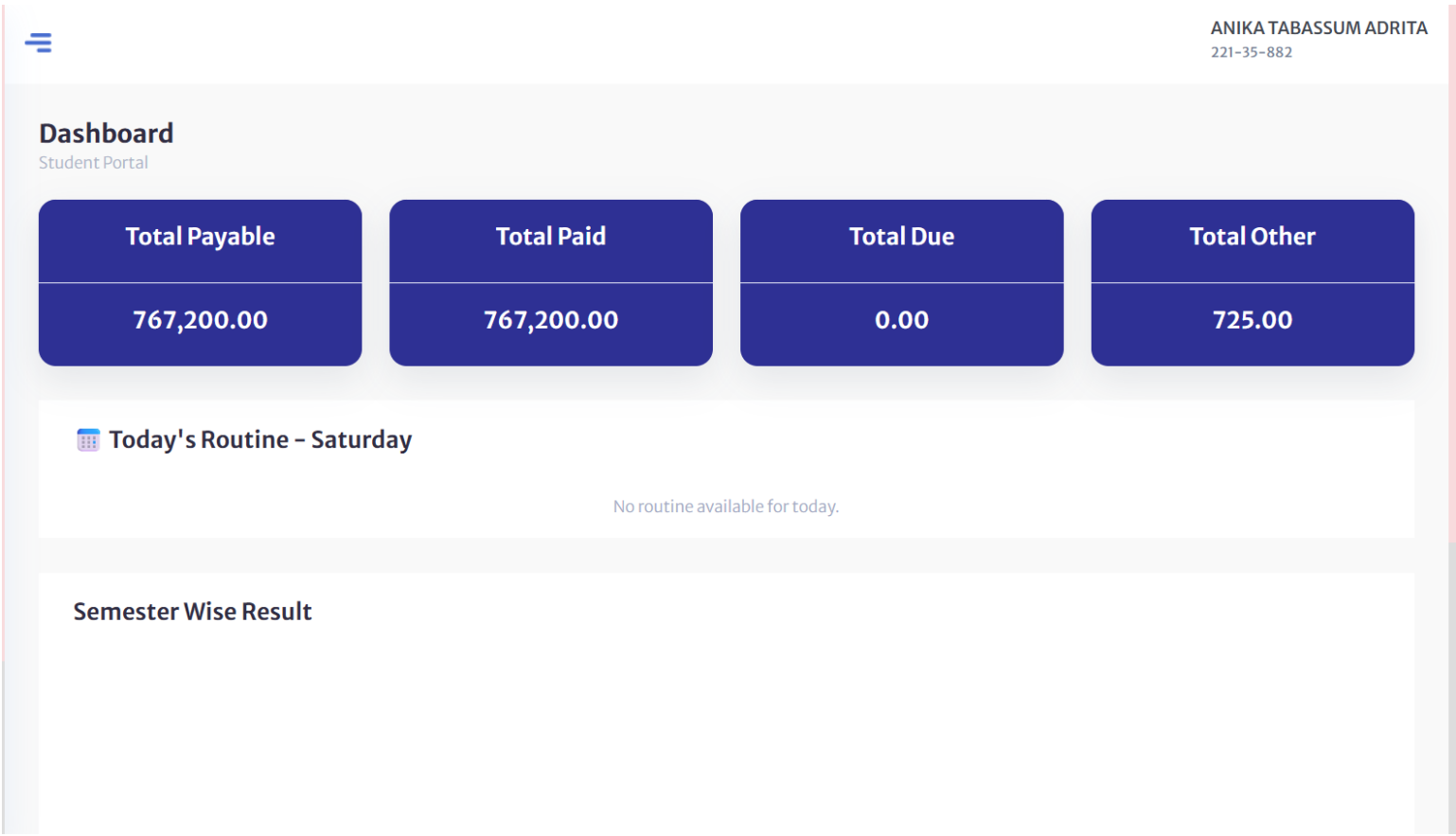
68	"Deep Learning and Convolutional Neural Networks for Medical Imaging and Clinical Informatics", Springer Science and Business Media LLC, 2019 Publication	<1 %
69	Anggi Muhammad Rifai, Suwanto Raharjo, Ema Utami, Dhani Ariatmanto. "Analysis for diagnosis of pneumonia symptoms using chest X-ray based on MobileNetV2 models with image enhancement using white balance and contrast limited adaptive histogram equalization (CLAHE)", Biomedical Signal Processing and Control, 2024 Publication	<1 %
70	Ben Othman Soufiene, Chinmay Chakraborty. "Machine Learning and Deep Learning Techniques for Medical Image Recognition", CRC Press, 2023 Publication	<1 %
71	Chengze Ye, Linda-Sophie Schneider, Yipeng Sun, Mareike Thies, Siyuan Mei, Andreas Maier. "DRACO: differentiable reconstruction for arbitrary CBCT orbits", Physics in Medicine & Biology, 2025 Publication	<1 %
72	Jennifer A. Steeden, Michael Quail, Alexander Gotschy, Kristian H. Mortensen et al. "Rapid whole-heart CMR with single volume super-resolution", Journal of Cardiovascular Magnetic Resonance, 2020 Publication	<1 %

73	Qiu, Bocheng. "Multi-Needle Fiberoptic Raman Spectroscopy Technique for Simultaneous Multi-Site Deep Tissue Raman Measurements", National University of Singapore (Singapore), 2025 Publication	<1%
74	Shubham Sharma, Arvind Selwal. "Potential of artificial intelligence in deepfake media: From generation to detection mechanisms, state-of-the-art, and challenges", Computer Science Review, 2026 Publication	<1%
75	Weiwen Wu, Xiaodong Guo, Yang Chen, Shaoyu Wang, Jun Chen. "Deep Embedding-Attention-Refinement for Sparse-View CT Reconstruction", IEEE Transactions on Instrumentation and Measurement, 2023 Publication	<1%
76	eprint.iitd.ac.in Internet Source	<1%
77	eprints.uthm.edu.my Internet Source	<1%
78	epub.uni-regensburg.de Internet Source	<1%
79	etd.aau.edu.et Internet Source	<1%
80	etheses.bham.ac.uk Internet Source	<1%
81	github.com Internet Source	<1%

82	gyan.iitg.ac.in Internet Source	<1%
83	hal.science Internet Source	<1%
84	ijarcce.com Internet Source	<1%
85	impa.usc.edu Internet Source	<1%
86	journalofbigdata.springeropen.com Internet Source	<1%
87	www.springerprofessional.de Internet Source	<1%
88	Leuschner, Johannes. "Deep Learning for Computed Tomography Reconstruction Learned Methods, Deep Image Prior and Uncertainty Estimation", Universitaet Bremen (Germany) Publication	<1%
89	ir.cwi.nl Internet Source	<1%
90	Arvind Dagur, Sohit Agarwal, Dhirendra Kumar Shukla, Shabir Ali, Sandhya Sharma. "Artificial Intelligence and Sustainable Innovation - Volume 3", CRC Press, 2026 Publication	<1%
91	Feng Wang, Renfang Wang, Hong Qiu. "Low-dose CT reconstruction using dataset-free learning", PLOS ONE, 2024 Publication	<1%

92	Gaoyu Chen, Xiang Hong, Qiaoqiao Ding, Yi Zhang et al. "AirNet: Fused analytical and iterative reconstruction with deep neural network regularization for sparse-data CT", Medical Physics, 2020 Publication	<1%
93	Udara Yedukondalu, V Vijayasri Bolisetty. "Advancing Innovation through AI and Machine Learning Algorithms - Computational Intelligence for Virtual System Optimization. A proceeding of ICMVRCET – 2025", CRC Press, 2025 Publication	<1%
94	Wei Wang, Jiayu Xia, Gongning Luo, Suyu Dong, Xiangyu Li, Jie Wen, Shuo Li. "Diffusion model for medical image denoising, reconstruction and translation", Computerized Medical Imaging and Graphics, 2025 Publication	<1%

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	Off		


ANIKA TABASSUM ADRITA
221-35-882
Dashboard
Student Portal
Total Payable
767,200.00
Total Paid
767,200.00
Total Due
0.00
Total Other
725.00
Today's Routine – Saturday
No routine available for today.
Semester Wise Result