CSCA 5642 Final Project

Convolutional Neural Networks for Photoelectric-Compton Decomposition in Duel-Energy CT Tissue Classification

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INTRODUCTION

Introduction

- Goal: Create a DL-spectral CT model to accurately “recover” three-tissue images.
- Models:
  - 11 convolutional layers (Unet256) and
  - 15 convolutional layers (UNet512)

METHODOLOGY

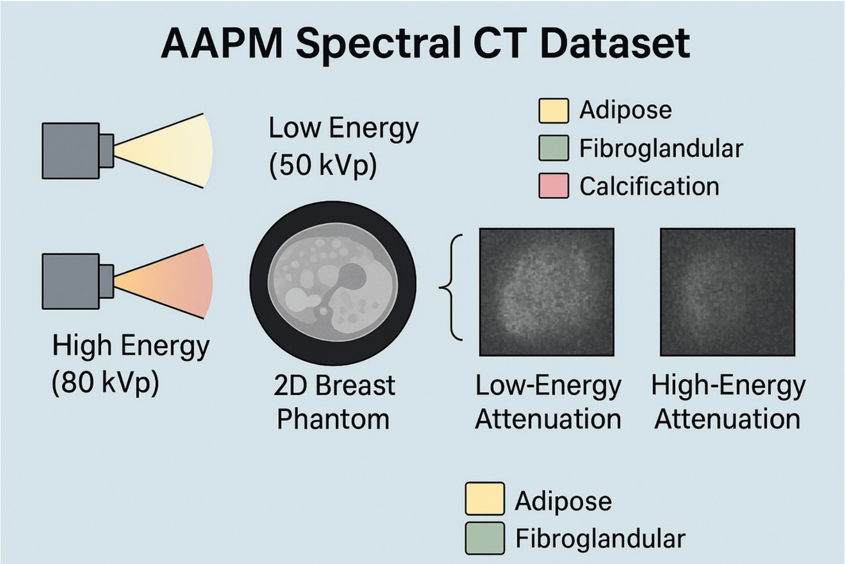
Methodology
Dataset

Duel-Energy CT Scan (Spectral CT)

- Low Energy 50kVp
- High Energy 80kVp

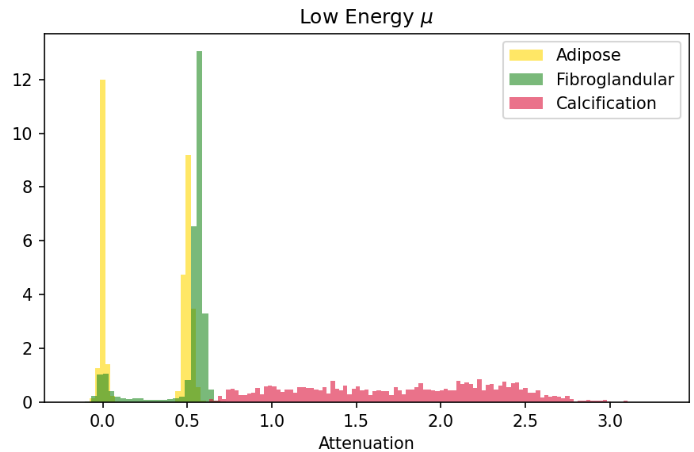
Dataset – for 50 & 80 kVp

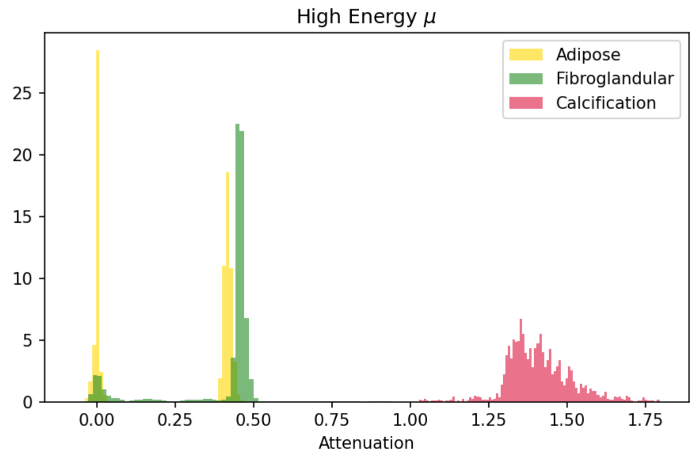
- 1000x512x512 True Tissue Values
- 1000x256x1024 kVp Transmission

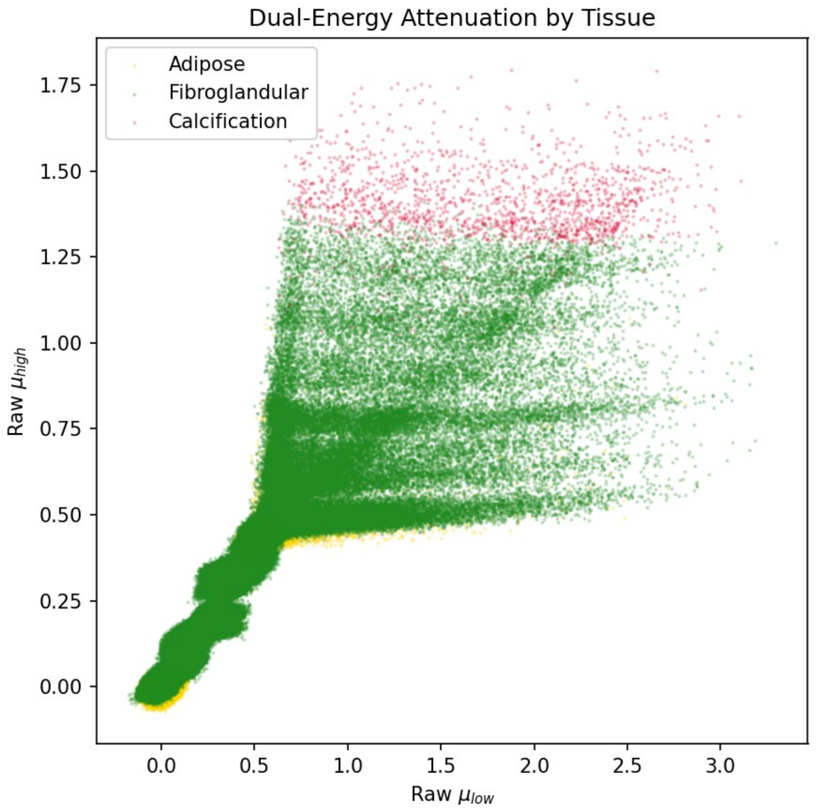


Methodology

Exploratory Data Analysis

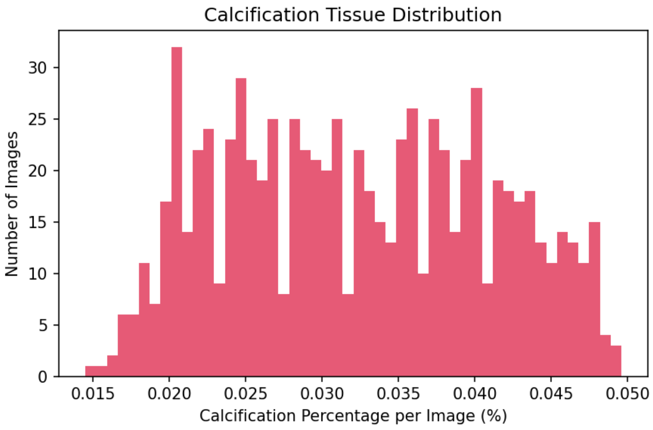


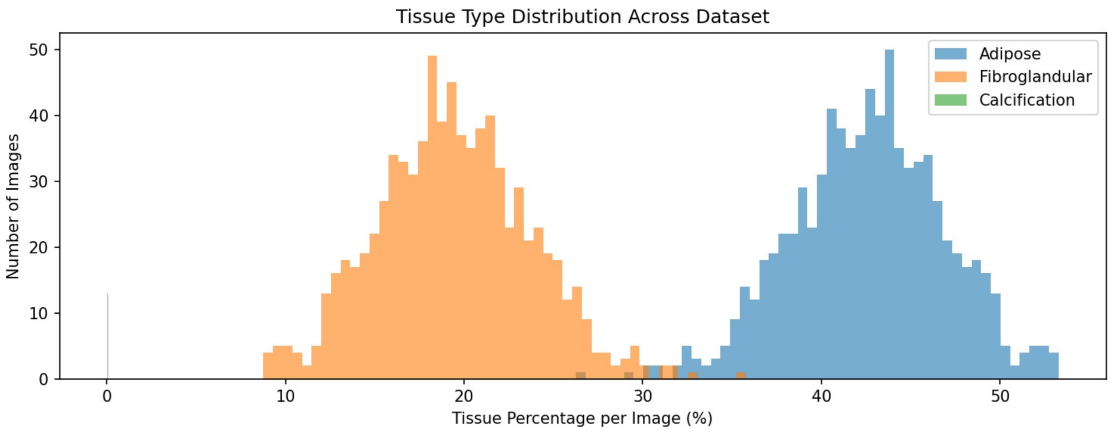




Methodology

Exploratory Data Analysis

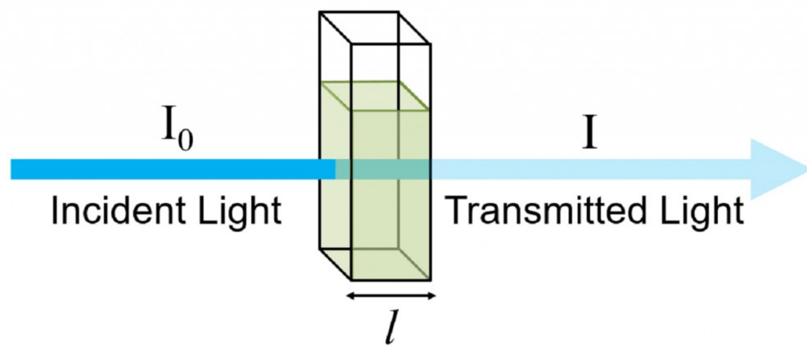




Methodology

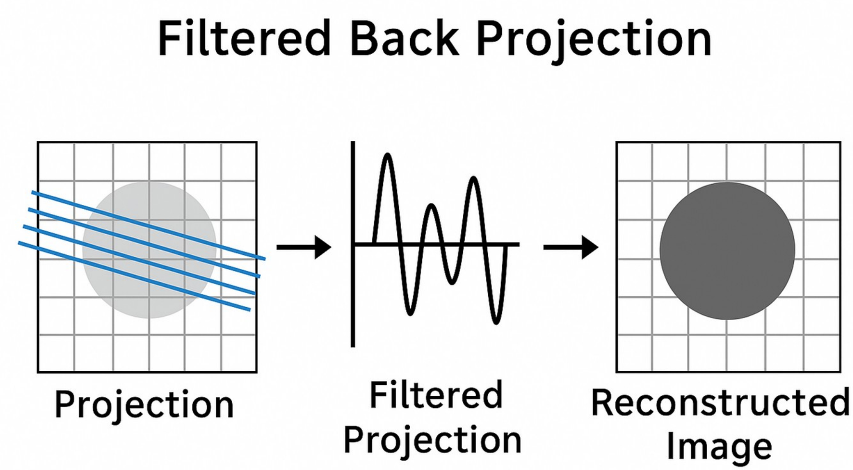
Data Preparation

Convert the transmission data into Attenuation values.



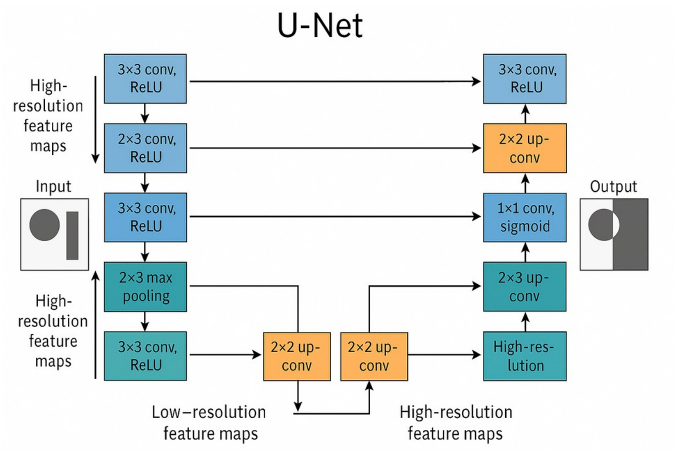
$$A = log_{10}\left(\frac{I_o}{I}\right) = \epsilon c l$$

Use Filtered BackProjection (FBP) to reconstruct kVp Images from Attenuation values [μ_{low}, μ_{high}].



Methodology

Models




```python
class ConvBlock(nn.Module):
    def __init__(
        self,
        in_channels,
        out_channels,
        kernel_size=3,
        padding=1
    ):
        super().__init__()
        self.block = nn.Sequential(
            nn.Conv2d(in_channels, out_channels, kernel_size=kernel_size, padding=padding),
            nn.ReLU(inplace=True),
            nn.Conv2d(out_channels, out_channels, kernel_size=kernel_size, padding=padding),
            nn.ReLU(inplace=True),
        )

    def forward(self, x):
        return self.block(x)
```

UNet256

- 2 encoding and decoding levels
- Encodes up to 256 pixels
- Faster to train but likely less expressive

UNet512

- 3 encoding and decoding levels
- Encodes up to 512 pixels
- Potential to recorder greater image complexity.

EVALUATION & ANALYSIS

Evaluation & Analysis

Hyperparameter Optimization

Tuned Hyperparameters

- **Filter Size**: 3, 4, 5
- **Stride**: 2, 3
- **Padding**: 1, 2
- **Learning Rate**: 1e-4, 1e-3, 1e-2
- **Batch Size**: 4, 8
- **Epochs:** 3, 5

Best Configurations

- UNet256: [Val Loss: 0.0519]
  - Filter Size: 4
  - Stride: 3
  - Padding: 2
  - Learning Rate: 0.001
  - Batch Size: 4
- UNet512: [Val Loss: 0.0380]
  - Filter Size: 5
  - Stride: 3
  - Padding: 1
  - Learning Rate: 0.001
  - Batch Size: 4

Evaluation & Analysis
Final Training Results

Epoch	Train Loss	Val Loss	MAE (Adipose, Fibro, Calc)
1	0.2254	0.0456	(0.00420, 0.00260, 0.00023)
2	0.0478	0.0366	(0.00469, 0.00469, 0.00010)
3	0.0365	0.0331	(0.00161, 0.00175, 0.00005)
4	0.0324	0.0310	(0.00216, 0.00260, 0.00004)
5	0.0304	0.0292	(0.00260, 0.00278, 0.00003)

Loss Curves

- Train Loss: Decreased from 0.2254 to 0.0304
- Val Loss: Dropped from 0.0456 to 0.0292 over 5 epochs.

Epoch	Predicted (%)			Ground Truth (%)		
	Adipose	Fibro	Calc	Adipose	Fibro	Calc
1	39.35	22.46	0.06	39.67	22.35	0.04
2	40.12	21.89	0.03	39.67	22.35	0.04
3	39.51	22.52	0.05	39.67	22.35	0.04
4	39.83	22.14	0.05	39.67	22.35	0.04
5	**39.42**	**22.61**	**0.04**	**39.67**	**22.35**	**0.04**

Evaluation & Analysis

Interpretation

Key Takeaways

- UNet512 Outperforms UNet256
- Model converges quickly
- High tissue composition accuracy

Challenges & Considerations

- Class imbalance
- Low error doesn’t guarantee clinical interpretability

Conclusion

UNet512 demonstrates effective learning of dual-energy spectral features for multi-tissue segmentation in noiseless 2D breast CT.

CONCLUSIONS

Conclusion
Results Summary

- UNet 512 achieved the best performance
  - Final validation loss: 0.0292
  - Tissue MAE: as low as <0.003
  - Tissue compositions closely matched ground truth
- Demonstrated robust performance despite class imbalance and small calcification signals

Conclusion
Key Contributions

- Integrated Beer-Lambert attenuation law into training design
- Used physically meaningful [μ_{low}, μ_{high}] features for segmentation
- Trained and evaluated fully end-to-end U-Net models on simulated AAPM data

Conclusion
Future Directions

- Add data augmentation or class balancing for rare tissue types (e.g., calcification)
- Extend model to noisy or real clinical data
- Explore multi-task learning (e.g., decomposition + classification)