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# Synthetic CT Generation from MRI

A Unet Deep Learning Approach

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October 16, 2024



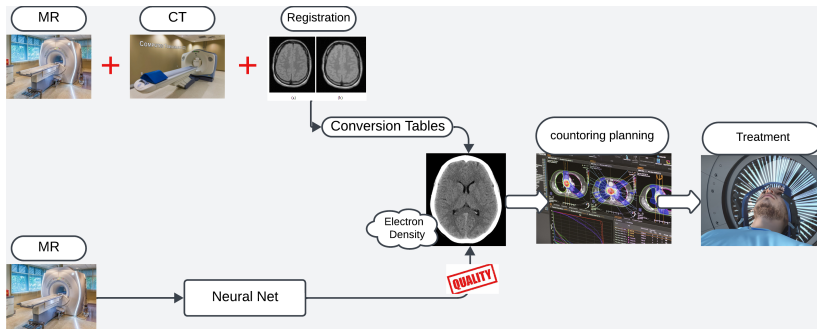
1. Introduction
2. Preprocessing
3. Data Augmentation
4. 2D U-Net Model
5. Testing Process
6. Results

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# Introduction



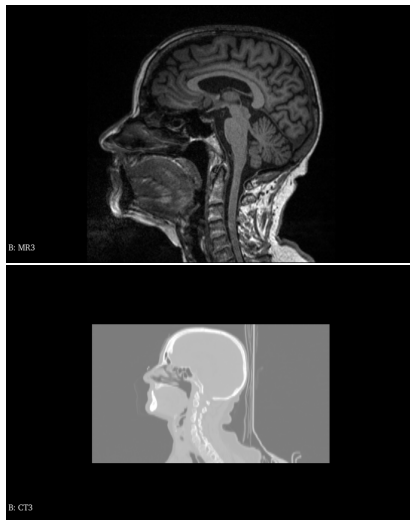
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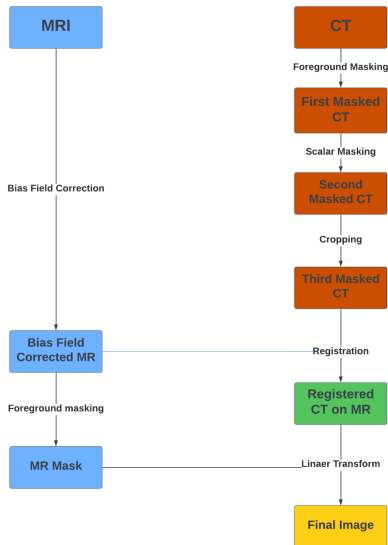
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## Datasets and Normalization

- Baseline Dataset: Glioma patients (3T MAGNETOM Trio, Siemens).
- Target Dataset: Neurodegenerative patients (SIEMENS Biograph mMR, PET/MRI hybrid).
- Z-score normalization was applied to MR images of both datasets.



# Preprocessing Workflow



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## Why Augment?

- Limited data in medical imaging leads to overfitting and biased models.
- Augmentation increases dataset diversity, crucial for model generalization.
- Our datasets: Baseline (15 patients) and Target (16 patients).

## Augmentation Methods

- Translation: Shifts image in different directions.
- Flip: Mirrors images horizontally or vertically.
- Horizontal and Vertical Flip: Rotates images 180 degrees for full orientation coverage.
- Rotation: Rotates images to add orientation diversity.
- Scaling: Resizes images to simulate different distances.

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# 2D U-Net Model Architecture



Block	Layers
Down 1	Conv2D + ReLU + BN + MaxPool
Down 2	Conv2D + ReLU + BN + MaxPool
Down 3	Conv2D + ReLU + BN + MaxPool
Down 4	Conv2D + ReLU + BN + MaxPool
Bottleneck	Conv2D + ReLU + BN + Conv2D + ReLU + BN
Up 1	Conv2D + ReLU + BN + ConvTransp
Up 2	Conv2D + ReLU + BN + ConvTransp
Up 3	Conv2D + ReLU + BN + ConvTransp
Output	Conv2D + ReLU + BN + Conv2D

Table: 2D U-Net Model Layers

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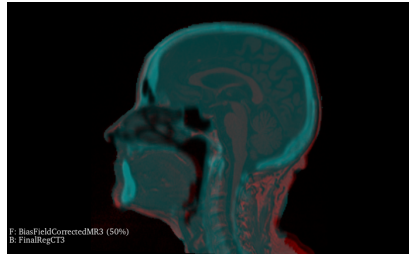
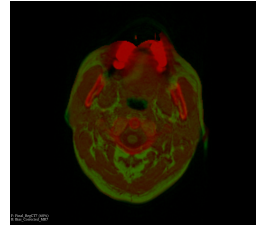
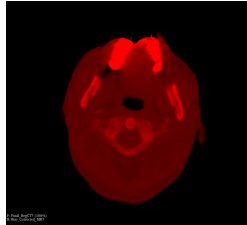
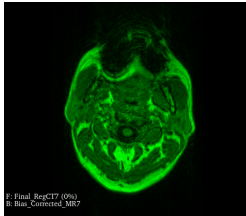
- **Comparison:** Predictions of synthetic CT images are compared with actual CT images in a defined region of interest (ROI) using a mask.
- **Metrics:**
  - **MAE (Mean Absolute Error):** Measures the average absolute difference between predicted and actual Hounsfield Unit (HU) values, indicating overall precision.
  - **BIAS (Mean Error):** Shows whether predictions overestimate or underestimate actual CT values.
  - **DSC (Dice Similarity Coefficient):** Evaluates the overlap between predicted and actual segmentations for specific tissue classes (e.g., bones, fat, muscle).

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# Preprocessing Results: Artifacts vs Normal

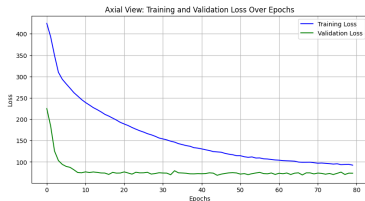


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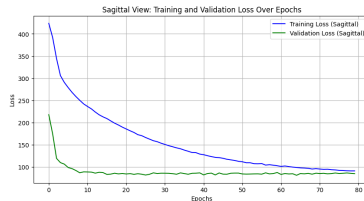




# Pretraining Results

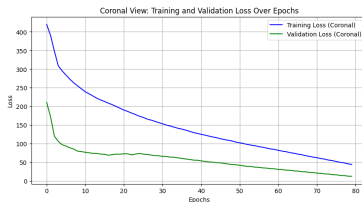


Axial View



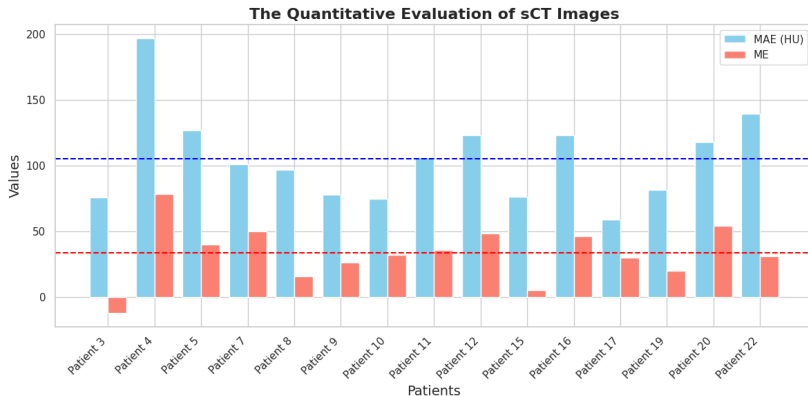
Sagittal View

$$(\text{MAE}) = 60.437, \text{ME} = 19.909$$



Coronal View

# Quantitative Evaluation: The Target Dataset

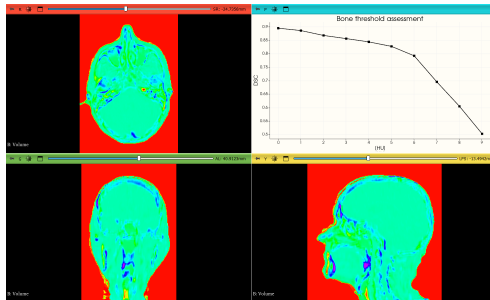


- Evaluated accuracy of sCT images using bone threshold assessment.
- Dice Similarity Coefficient (DSC) measures overlap between sCT and CT bone structures.
- DSC ranges from 0 (no overlap) to 1 (perfect overlap).
- DSC decreases as Hounsfield Unit (HU) thresholds increase.
- Higher DSC at lower HU indicates better bone structure capture in sCT.
- Decline in DSC at higher HU reflects challenges in modeling dense bone tissues.

# Bone Threshold Assessment: Sample Case



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**Sample Case:** This figure illustrates the comparison between real CT and sCT for a specific case (P3), showing the impact of HU threshold variation on bone structure accuracy.

# Thanks!