3D Anatomy Reconstruction

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https://github.com/ratnadeepika27/cs668-3d-anatomy-reconstruction

Abstract

Reconstructing incomplete 3D anatomical structures is critical for applications in medical imaging, 3D bioprinting, and forensic science. This project explores deep learning models, including 3D GAN, 3D U-Net, and Denoising Autoencoders (DAEs), to automate the completion of missing anatomical structures. This work highlights the potential of deep learning to improve efficiency and accuracy in 3D anatomy reconstruction, offering significant advancements for healthcare and scientific applications.

Research Questions

- How accurately can a deep learning model reconstruct missing 3D anatomical structures?
- Can the model generalize across different types of anatomy (e.g., bones, organs, tissues)?
- What are the optimal deep learning techniques for high-fidelity 3D anatomy completion?

Dataset

Dataset:

- The dataset used in this project is derived from the TotalSegmentator collection, which is designed for comprehensive anatomical segmentation in medical imaging.
- It contains 3D CT images segmented into 104 anatomical structures, including **27 organs** like the heart, liver, and lungs, **59 bones** such as the femur, skull, and vertebrae, along with **10 muscles** and **8 vessels**.
- The dataset reflects real-world diversity, incorporating a wide range of pathologies, imaging scanners, and sequences from various institutions, making it highly robust and clinically relevant.

Subset Used:

- A subset of 102 subjects was selected to enable quick experimentation while maintaining the diversity and complexity of the full dataset for clinically relevant training.
- The dataset reflects real-world medical imaging scenarios, ensuring that results are applicable to practical settings.
- It includes major anatomical structures, making it an ideal benchmark for evaluating deep learning models in 3D anatomy reconstruction.

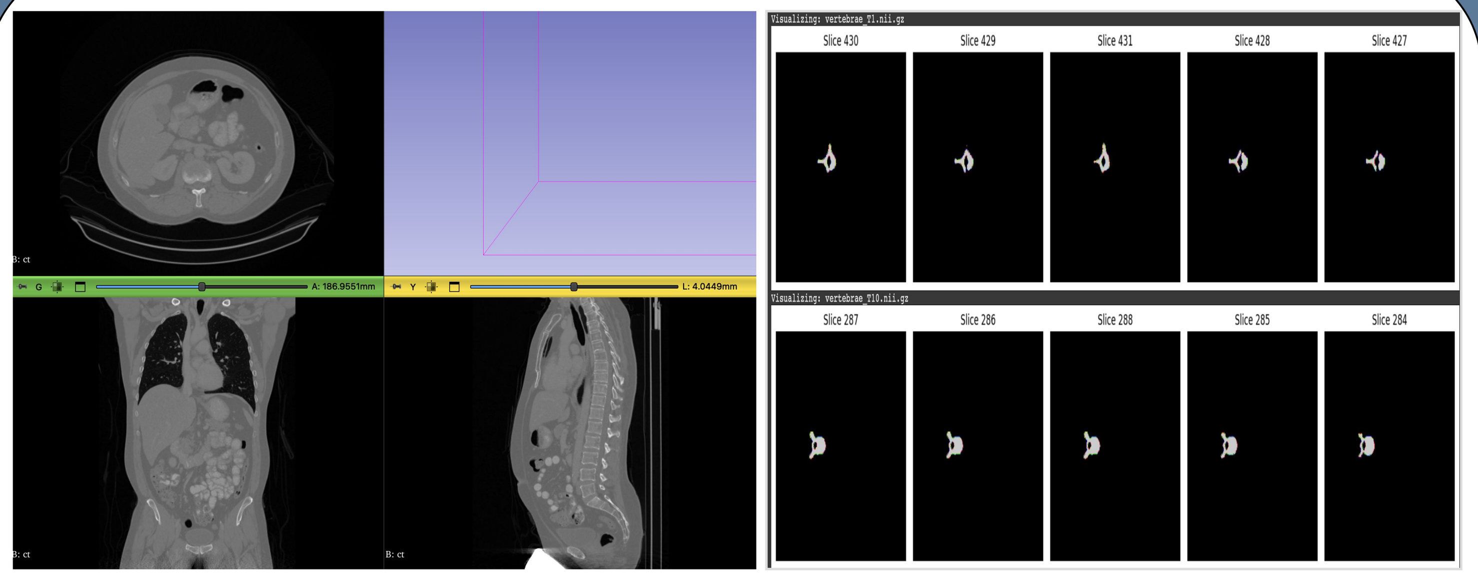


Figure: The image on the left showcases sliced views of a CT scan from different angles, providing a detailed visualization of the overall anatomy. On the right, sliced views of the adrenal gland (left and right parts) are displayed, highlighting the specific organ of interest within the anatomical structure.

Methodology

To tackle the challenge of reconstructing incomplete 3D anatomical structures, we developed a step-by-step approach using advanced deep learning techniques. Our methodology covers everything from preparing the data to training and evaluating the models, ensuring a thorough and reliable process. We chose three models—3D U-Net, 3D GAN, and Denoising Autoencoder (DAE)—because each brings unique strengths. Together, they help us balance accuracy, realism, and the ability to handle noisy or missing data. Every step was designed with the goal of creating practical, clinically relevant solutions that can effectively reconstruct even the most challenging anatomical structures.

1. Data Preparation:

- The dataset, containing 3D CT scans and corresponding anatomical segmentations, are Medical imaging files in `.nii.gz` format are processed using nibabel and NumPy.
- Preprocessing includes extracting, normalizing, and visualizing slices of CT scans and segmentation masks to ensure data quality.
  - A subset of 102 subjects is selected for efficient experimentation balancing data diversity and computational feasibility.

2. **Model Implementation:**

- **3D U-Net**: Implemented with an encoder-decoder structure using 3D convolutions, ReLU activations, and skip connections for spatial detail retention. Trained with cross-entropy loss, Adam optimizer (learning rate: 0.001), and data augmentation for better generalization.
- **3D GAN**: Comprises a generator with 3D transposed convolutions and a discriminator with 3D convolutions. Used binary cross-entropy loss for adversarial training, with alternating updates via Adam optimizer (learning rates: 0.0002 and 0.0001).
- **DAE**: Encoder-decoder design to denoise and reconstruct missing structures. Trained with MSE loss and Adam optimizer (learning rate: 0.001) using artificially generated noisy data.

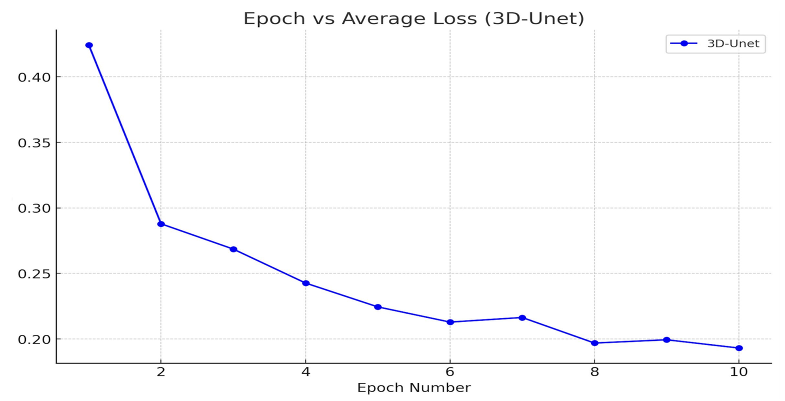
3. Training and Evaluation:

- The models are trained on the subset of the dataset, with hyperparameters optimized for handling 3D volumetric data.
- Performance is evaluated using metrics such as Dice Coefficient, Fréchet inception distance, and Inception Score, ensuring the outputs align with the ground truth.

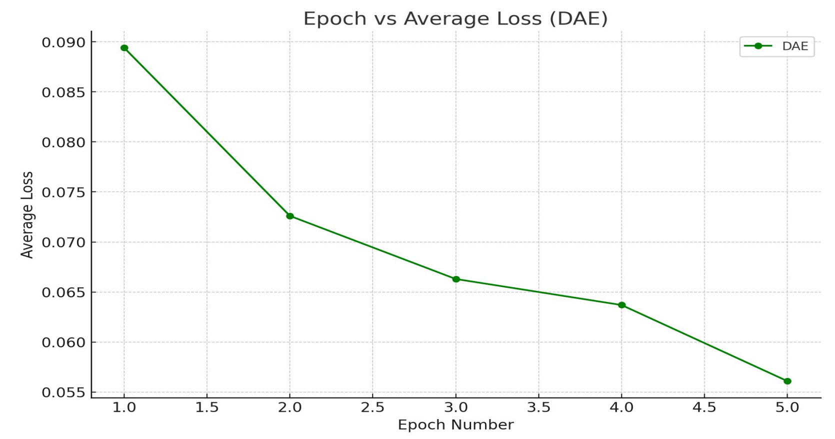
Results

The models were trained and evaluated to assess their performance in reconstructing 3D anatomical structures. After training for 10 epochs, the following results were obtained:

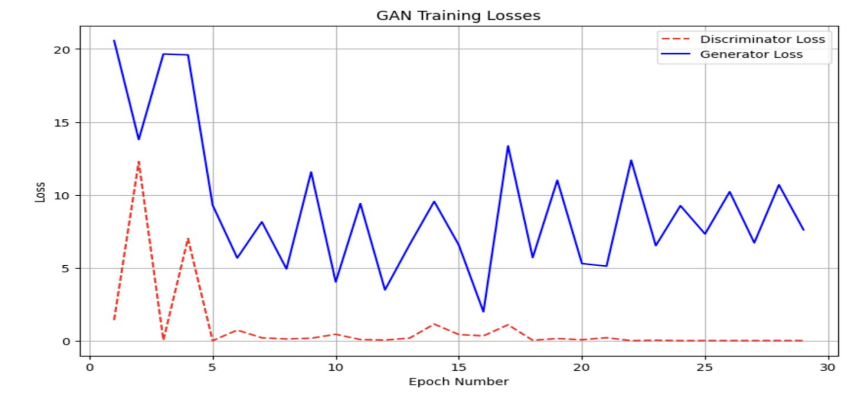
- **3D U-Net**:
- Achieved a Dice coefficient of 78.07%, indicating a good accuracy in reconstructing anatomical structures



- **Denoising Autoencoder (DAE)**:
- Achieved a Dice coefficient of 77.77%, showing slightly better performance in segmentation and reconstruction tasks.



- **3D GAN**:
- A Fréchet Inception Distance (FID) score of 58.4, reflecting the quality of the generated outputs compared to real data.
- An Inception Score (IS) of 4.92, indicating reasonable diversity and realism in the generated anatomical structures.



Conclusion & Future Work

This study demonstrates the potential of deep learning models in reconstructing 3D anatomical structures from incomplete data. The 3D U-Net and DAE models achieved good segmentation accuracy, with Dice coefficients of 78.07% and 77.77%, respectively, showcasing their ability to handle spatial details and denoise input data effectively. The 3D GAN exhibited promising results in generating visually realistic outputs, as reflected in its FID score of 58.4 and IS score of 4.92. While the models successfully reconstructed anatomical structures, the results indicate room for improvement.

In Future we will focus on the following Aspects to Improve the model:

- Optimize model architectures with attention mechanisms and hybrid loss functions to enhance performance.
- Expand the dataset to include diverse anatomical structures and pathologies for better generalization.
- Integrate advanced evaluation metrics for comprehensive assessment of reconstruction quality.
- Combine the strengths of 3D U-Net, GAN, and DAE for balanced accuracy and realism.

References

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