Automatic Atrium Segmentation with Machine Learning

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Background

- **Objective:** Develop a machine learning model and pipeline for automatic 3D segmentation of the left atrium in patients with atrial fibrillation.
- **Clinical Motivation:**
  - **Atrial fibrillation** is a prevalent cardiac condition.
  - **Accurate segmentation of atrial regions** in 3D imaging **improves diagnosis and treatment.**
  - Manual segmentation is **time-consuming** and **subject to variability.**
  - Automatic methods using **machine learning** and **3D meshes** could offer better efficiency and accuracy.

Related Work

- ***Graph U-Nets***
  - **Objective:** Improving graph neural network performance on node and graph classification tasks.
  - **Methodology:** U-Net like graph pooling (**gPool**) and unpooling (**gUnpool**) operations to improve performance on node and graph classification tasks.
  - **Results:** High accuracy on across multiple node and graph classification benchmarks (e.g. Cora dataset).
- ***Dynamic Graph CNN for Learning on Point Clouds***
  - **Objective:** Improving point classification and segmentation without using handcrafted features.
  - **Methodology:** Generate embeddings for each edge and feed these into existing deep learning models (e.g. PointNet).
  - **Results:** The model achieved state-of-the-art performance on benchmark datasets, such as an overall accuracy of **92.9%** on ModelNet40.
- ***Dense graph convolutional neural networks on 3D meshes for 3D object segmentation and classification***
  - **Objective:** Building a more efficient design for 3D object segmentation.
  - **Methodology:** Usage of a MDC-GCN for 3D segmentation consisting of 2 DC blocks and 3 GCN layers.
  - **Results:** The proposed model was able to keep up with the state-of-the-art in 3D segmentation and has fewer parameters than the known approaches.
- ***MeshCNN: A Network with an Edge***
  - **Objective:** To design a convolutional neural network (CNN) specifically for analyzing 3D shapes represented as polygonal meshes.
  - **Methodology: MeshCNN** uses specialized convolution and pooling layers that operate on mesh edges, utilizing their intrinsic geodesic connections.
  - **Results:** MeshCNN demonstrates effective performance on various learning tasks applied to 3D meshes, outperforming traditional methods by focusing on important features and discarding redundant ones.

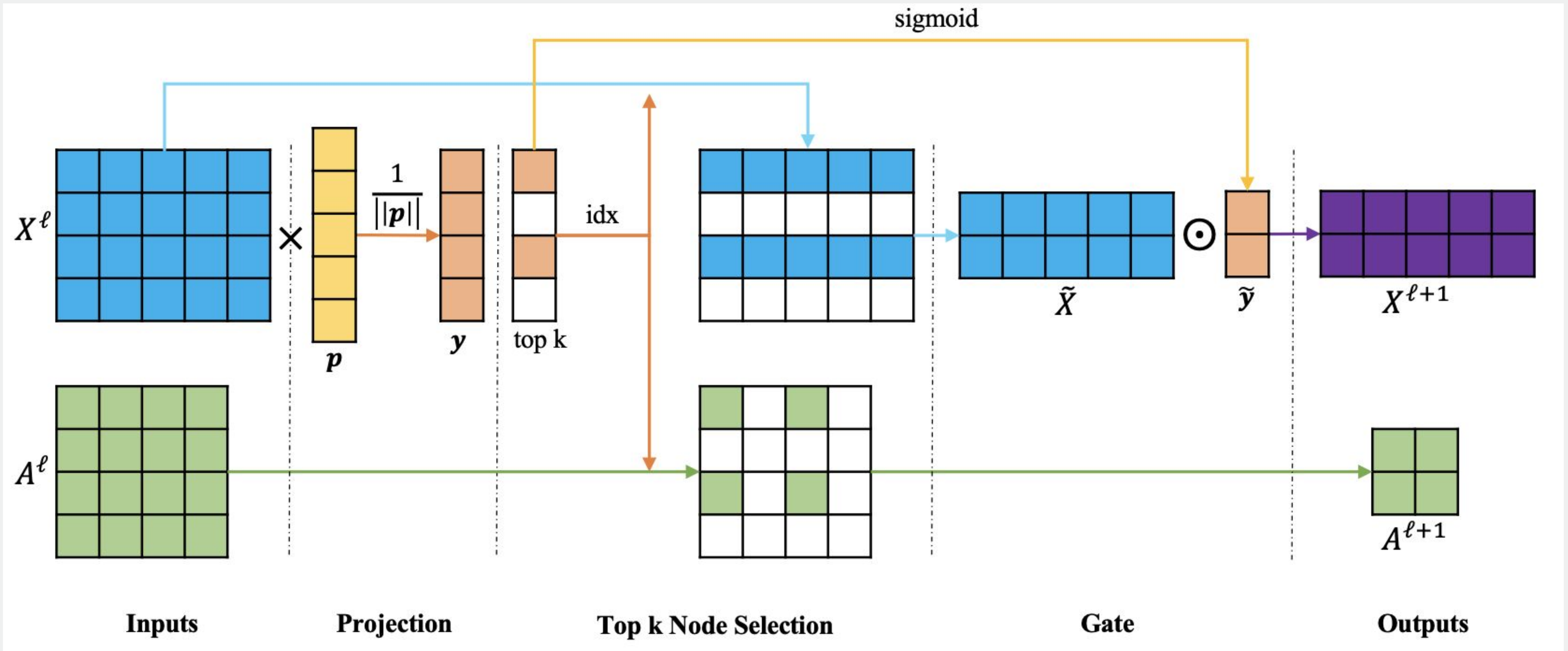

Figure 1: Structure of a *Graph U-Net*

Methodology

- **Experimental Setup:**
  - **Data Sources:** Electroanatomical mapping data from local hospitals.
  - **Tools and Frameworks:**
    - Python, PyTorch, PyTorch Geometric, and VTK for visualization.
- **Data Preprocessing**:
  - **Input data:** 3D meshes with vertices, faces, and segmentation groups generated from electroanatomical mapping (and potentially MRI and CT scans).
  - **Normalization:** Standardized coordinates of vertices.
  - **Edges:** Compute edge index to emphasize relationships between vertices.
- **Pipeline and Methods Proposed:**
  - **Pipeline Overview:**
    - Load 3D meshes and preprocess data.
    - Input normalized data into a neural network for segmentation.
    - Compare predicted segmentations with manually annotated regions.
  - **Neural Network:**
    - Implemented a graph-based neural network using PyTorch Geometric, which is based on *Graph U-Nets*.
    - **Input features:** Vertex coordinates, graph edges.
    - **Output:** Class labels for each vertex (e.g., left atrium, pulmonary vein, or background).
    - **Architecture:** A Graph U-Net model with layers for feature extraction, pooling, and upsampling.
  - **Optimization Criterion:**
    - **Cross-Entropy Loss:** difference between the predicted probability distribution and the actual distribution (or true labels), used to evaluate the performance of classification for the vertices.

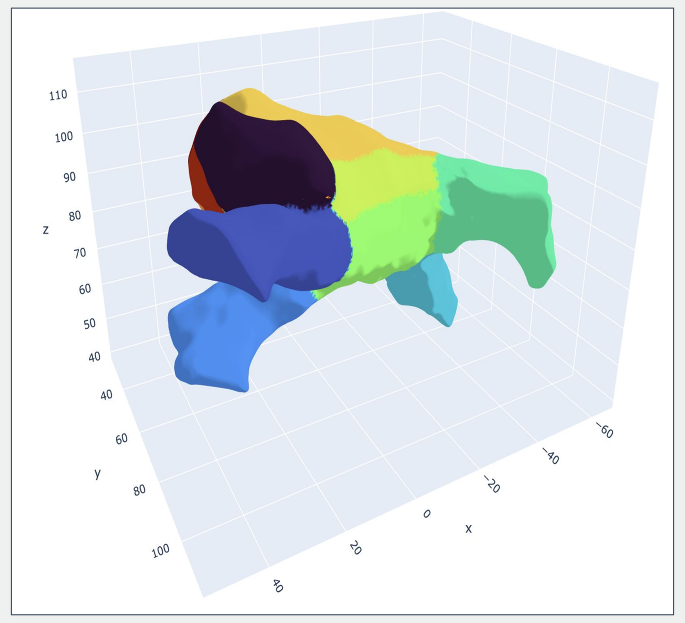

Figure 2: Initial visualization of manual atrium segmentation

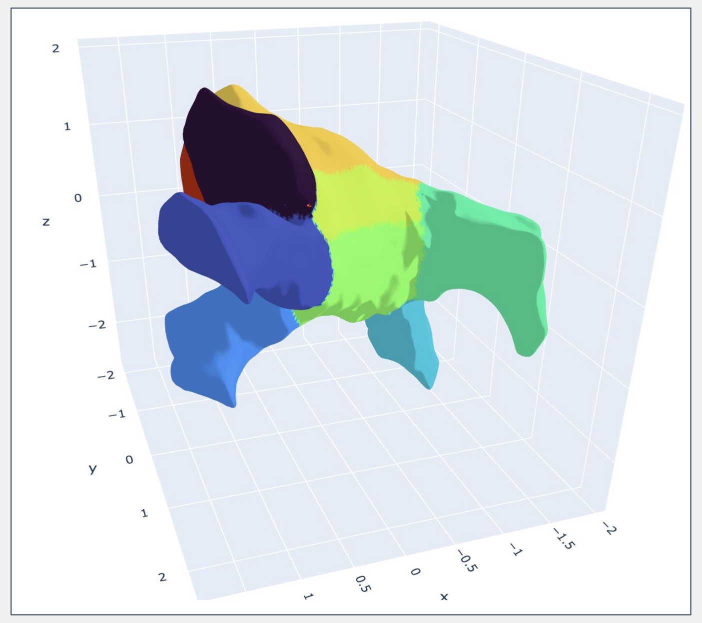

Figure 3: Visualization of preprocessed data with labels

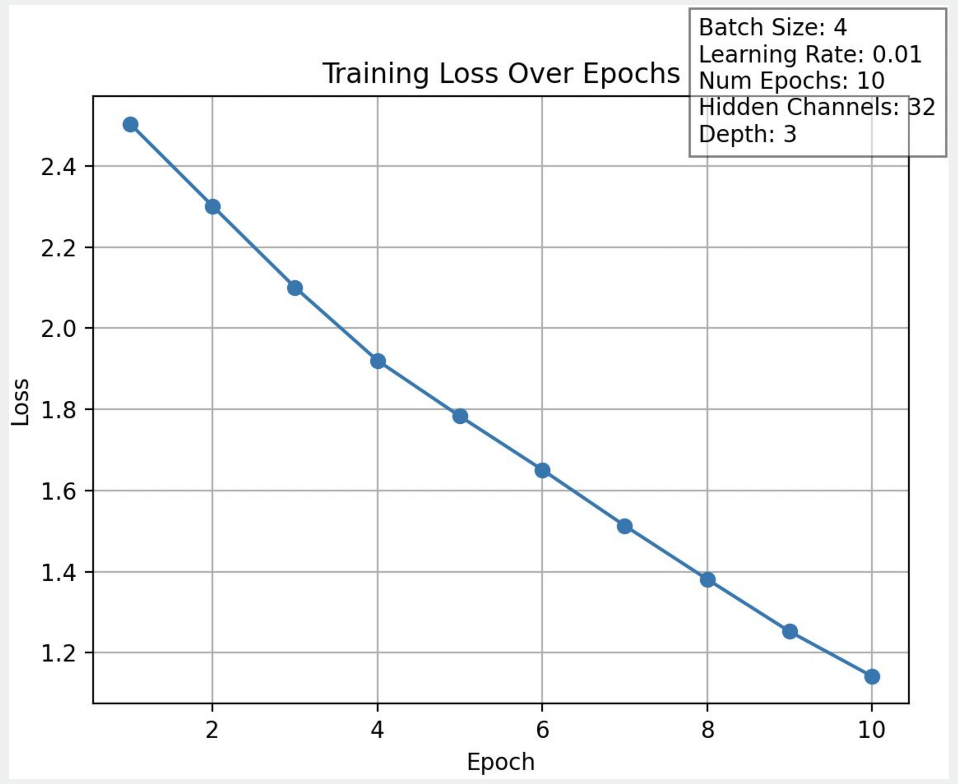

Figure 4: Training Loss Over Epochs
The model shows steady convergence, with training loss decreasing from 2.5 to 1.14 over 10 epochs, using a learning rate of 0.01 and **only 1% of the data to train the model.**

Results

- **Developed a functional preprocessing pipeline** to normalize and data and generate graph edges.
- **Trained initial machine learning model** with promising results on preprocessed meshes.
- **Generated 3D visualizations of segmented atrium region** for evaluation.
- **Limitations and Unfinished Goals**
  - Model performance **still requires improvement for generalization** across diverse datasets.
  - **Training data** from was limited, making cross-modality validation inconclusive.
  - **Computational limitations**, as we only ran the training locally.
  - **No deployment pipeline yet** for real-time or clinical usage.

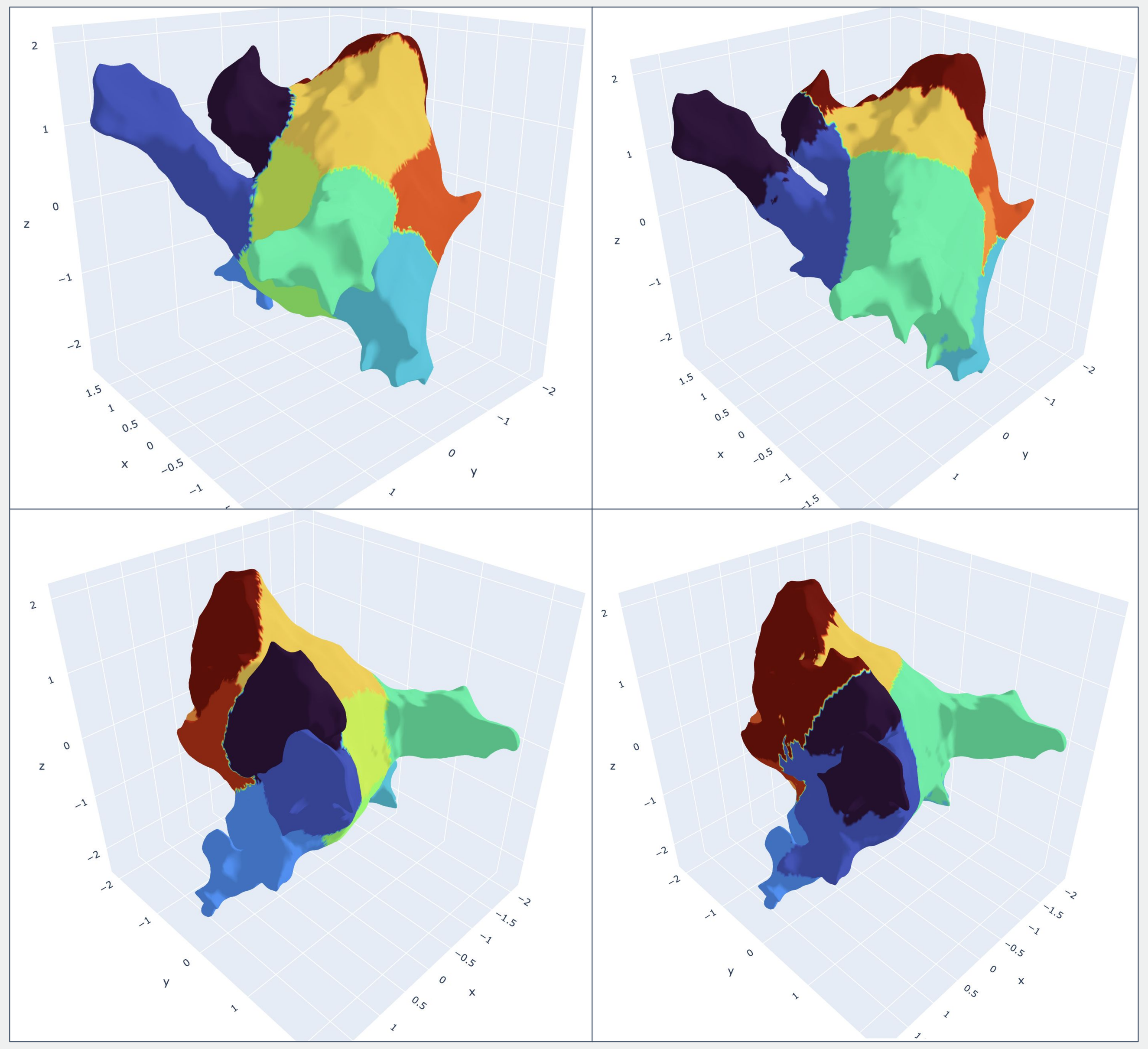

Figure 5: Two angles of sample visualization. Original atrium segmentation (left) and our predicted atrium segmentation (right)

Future Work

- **Prevent overfitting** (e.g. by training the model on a subset of features).
- Use **resampling** and check if parts of the data are corrupted to avoid processing errors.
- Use different evaluation metrics e.g., **Dice Similarity Coefficient** or **Hausdorff Distance** to properly evaluate the model.
- Apart from Graph U-Nets, other implementations such as **Graph CNNs** show promising results for 3D graph segmentation (see **Related Work**).

Conclusion

- Automated 3D atrium segmentation with machine learning can significantly reduce the workload for clinicians and improve the speed of diagnosis and treatment planning.

GitHub Repository

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