Attention U-Net: Learning Where to Look for the Pancreas

CS300 : Midsem Project Evaluation

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Problem Statement

- **Challenge**: Accurate segmentation of anatomical structures, such as the pancreas, in medical imaging remains an obstacle due to significant inter-patient variability in shape and size, low tissue contrast in CT scans, and the dependency on computationally intensive multi-stage convolutional neural networks (CNNs) that inefficiently localize regions of interest.
- **Goal**: Develop an innovative, single-model architecture—Attention U-Net—that integrates attention gates to autonomously emphasize salient features and suppress irrelevant regions, achieving enhanced segmentation precision with reduced computational overhead.

Literature Survey

1. **Ronneberger et al. (2015) — U-Net: Convolutional Networks for Biomedical Image Segmentation**
   - Created U-Net to segment 2D medical images with a shrink-and-expand design for clear details.
   - Set the foundation for 3D models, aiding pancreas segmentation in CT scans.

2. **Çiçek et al. (2016) — 3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation**
   - Upgraded U-Net to 3D for CT scans, linking slices for a full view.
   - Key for pancreas segmentation by capturing organ connections in 3D.

Literature Survey (Contd.)

3. **Milletari et al. (2016) — V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation**
    - Built V-Net for 3D CT/MRI scans, focusing on small organs like the pancreas.
    - Uses a smart scoring trick to handle uneven data, boosting accuracy.

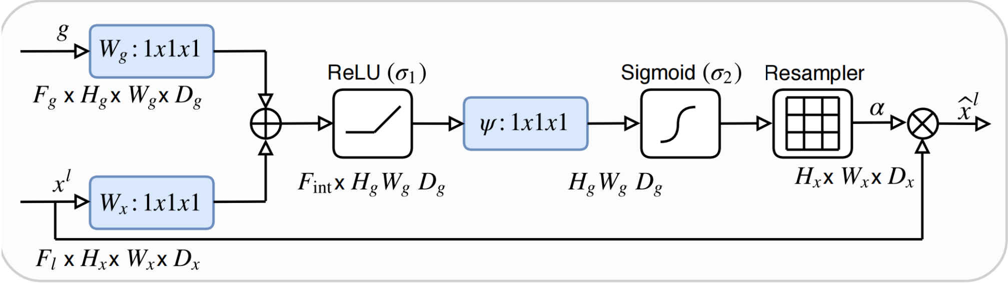
4. **Gibson et al. (2017) — Automatic Multi-Organ Segmentation with Dense Dilated Networks**
    - Designed a method to segment multiple organs in CT scans at once.
    - Helps separate pancreas from nearby organs with a wider view.

Research Focus: Attention U-Net - Learning Where to Look for the Pancreas

- **Medical Image Segmentation:** Divides CT scans into regions, identifying organs for diagnosis and treatment.
- **Pancreas Challenges:** Low tissue contrast, high inter-patient variability and proximity to organs (e.g., spleen, stomach) complicate localization, often causing poor boundary detection and overlap confusion.
- **Attention U-Net:** Builds on U-Net (Ronneberger, 2015) by adding **Attention Gates (AGs)** in the skip connections. AGs weigh features from the encoder with context from the decoder, focusing on pancreas regions and suppressing noise in one model. Cascaded CNNs stack networks, increasing computational overhead and requiring extra object localization modules.
- **Motivation:** AGs enhance efficiency and precision, avoiding the resource-heavy complexity of cascaded CNNs for the tricky pancreas.

Model Architecture

Main Paper Link: click here



Methodology: Attention Mechanism

1. **Input Processing:** Two parallel inputs:
   - **Local features** x_i^l from lower layers
   - **Gating signal** g_i from coarser scales
2. **Feature Transformation:** Both inputs undergo linear transformations via 1x1x1 convolutions:
$$W_x^T x_i^l \quad \text{and} \quad W_g^T g_i$$
3. **Feature Combination and Non-Linearity:** Additively combined and passed through ReLU:
$$\sigma_1(W_x^T x_i^l + W_g^T g_i + b_g)$$
4. **Attention Coefficients:** Transformed via linear mapping, normalized by sigmoid:
$$\alpha_i^l = \sigma_2\left(\psi^T \sigma_1(W_x^T x_i^l + W_g^T g_i + b_g) + b_\psi\right)$$
5. **Gated Output:** Final gated output via element-wise multiplication:
$$\hat{x}_{i,c}^l = x_{i,c}^l \cdot \alpha_i^l$$

Training Results from the Project Source Code

- **Dataset**: Pancreas CT-82 (TCIA), currently trained on its reduced version (60 patients out of total of 82)
- **Number of Epochs**: 70

Metric	Predicted 3D U-Net	Attention U-Net
Dice Score	65%–70%	81.5% ± 6.8%
Precision	67%–71%	81.5% ± 9.3%
Recall	68%–72%	83.5% ± 5.7%
S2S Distance (mm)	3.0–3.5	2.333 ± 0.856 mm

Future Improvement: Enhancing Attention U-Net

- **Limitation:** Single attention focus struggles with complex organ structures, leading to inaccurate segmentation of overlapping regions like the pancreas and spleen.
- **Proposed Upgrade:** Multi-Head Attention (MHA) assigns multiple attention heads to capture both fine-grained details and larger spatial relationships simultaneously.

  Example: Head 1 zeroes in on the pancreas-stomach interface. Head 2 focuses on the pancreas tail and its subtle overlap with the spleen's blood vessels. Head 3 captures the broader context, like how the pancreas aligns with the duodenum, ensuring the big-picture shape stays coherent.
- **Benefit:** Improves segmentation accuracy, enhances spatial awareness, and ensures better generalization across diverse medical scans with minimal computational overhead.
- **Current Progress:** I am improving my main model's performance, aiming for standard results, and then I plan to implement multi-head attention in my existing model.

Related Work: Hierarchical 3D Fully Convolutional Networks for Multi-Organ Segmentation

- **What They Did:** Used a 3D U-Net with a hierarchical two-step method, a **coarse-to-fine** approach to detect **seven abdominal organs** (artery, vein, liver, spleen, stomach, gallbladder, pancreas) in CT scans.
- **First Step:** Roughly outlines organs by scanning **40% of the image** with a **simple body mask** to focus on relevant regions, separating the background from the organs.
- **Second Step:** Zooms into **10% of the image** based on the first guess, sharpening edges for **precise boundaries**.
- **Key Wins:** Big accuracy boost for **small organs** and adapts to **new hospital testing data**.

Dice	liver	spleen	pancreas	liver	spleen	pancreas	liver	spleen	pancreas
Mean	93.6	89.7	68.5	94.9	91.4	81.2	95.4	92.8	82.2
Std	2.5	8.2	8.2	2.1	8.9	10.2	2.0	8.0	10.2
Median	94.2	91.8	70.3	95.4	94.2	83.1	96.0	95.4	84.5
Min	78.2	20.6	32.0	80.4	22.3	1.9	80.9	21.7	1.8
Max	96.8	95.7	82.3	97.3	97.4	91.3	97.7	98.1	92.2

Conclusion

In this project, a robust approach for pancreas segmentation from CT images was successfully developed leveraging advanced deep learning techniques.The methodology effectively addressed key challenges such as boundary ambiguity and class imbalance, achieving notable improvements in segmentation accuracy.

The results underscore the potential of AI-driven solutions in medical image analysis, paving the way for more precise and automated diagnostic tools. Future work may focus on enhancing model generalization across diverse datasets and integrating clinical insights to further refine segmentation performance.

References

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Thank You