Advancing Medical Imaging with Deep Learning: Pancreas Segmentation Insights

CS300 : Midsem Project Evaluation

Sreejita Das

Department of Computer Science and Engineering
Indian Institute of Information Technology, Guwahati

3 March, 2025

Problem Statement

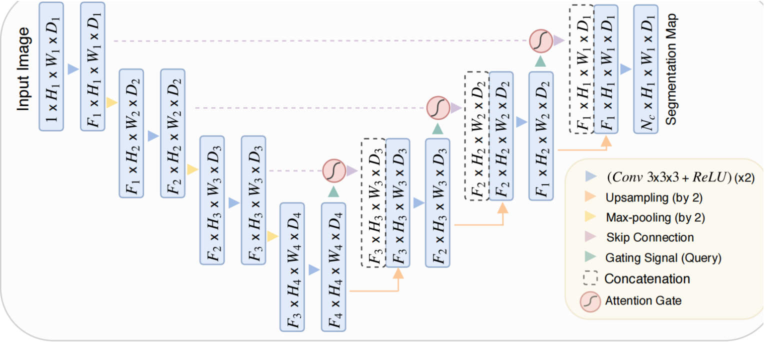
- **Challenges:** Pancreas segmentation is hindered by inter-patient variability, low contrast in CT scans, and proximity to adjacent organs (e.g., spleen, stomach).
- **Approach:** Attention U-Net incorporates attention gates into the U-Net architecture to prioritize pancreas features and minimize irrelevant background information.
- **Advantage:** This single-model solution enhances precision and efficiency, outperforming resource-intensive multi-stage CNNs.

Literature Survey

- **U-Net (Ronneberger, 2015):** Built a CNN for 2D medical image segmentation; basis for pancreas work in CT scans.
- **3D U-Net (Çiçek, 2016):** Adapted U-Net for 3D CT scans, connecting slices for full pancreas detail.
- **V-Net (Milletari, 2016):** Designed specifically for 3D volumetric data, for segmentation of small organs like the pancreas.
- **Dense Dilated Nets (Gibson, 2017):** Segments multiple organs in CT scans, utilizing dilated CNNs that capture the broader context for identifying multiple organs simultaneously.

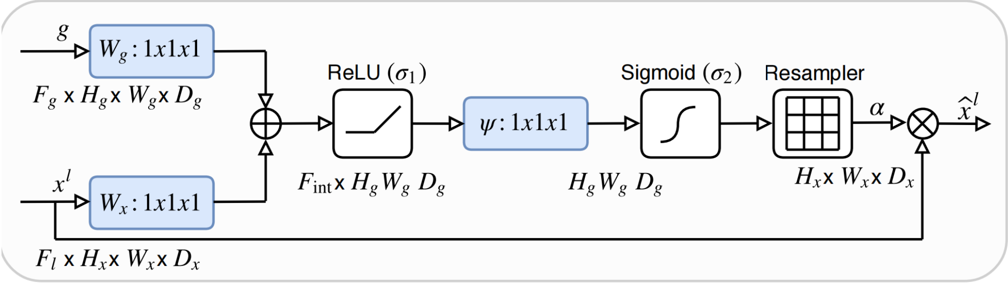
Research Focus: Attention U-Net - Learning Where to Look for the Pancreas

- **Medical Image Segmentation:** Divides CT, MRI, X-ray scans into regions, identifying organs for diagnosis and treatment.
- **Attention U-Net:** Builds on U-Net (Ronneberger, 2015) by adding **Attention Gates (AGs)** in the skip connections.



Model Architecture

Main Paper Link: click here



Methodology: Attention Mechanism

- **Input Processing:** Combines local features from finer layers and a gating signal from coarser scales.
- **Feature Combination:** Merges transformed inputs and passes it to ReLU for removing negative values.
- **Attention Coefficients:** Generates weights to emphasize pancreas features, by applying sigmoid function.
- **Gated Output:** Produces refined features, by combining attention scores with original features.

- **Why Not Cascaded CNNs?** Avoids their computational complexity and multi-stage overhead, along with the need fot separate image localization modules.

Training Results

- **Dataset:** Pancreas CT-82 (TCIA)
- **Patients:** 60 out of 82 total (till now)
- **Epochs:** 70 (till now)

Metric	Predicted	Actual
Dice Score	65%–70%	81.5% $\pm$ 6.8%
Precision	67%–71%	81.5% $\pm$ 9.3%
Recall	68%–72%	83.5% $\pm$ 5.7%
S2S Distance	3.0–3.5 mm	2.33 $\pm$ 0.86 mm

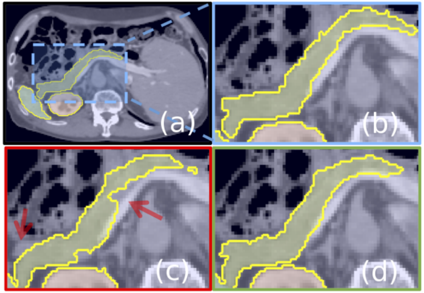


Figure 3(b): The ground-truth pancreas segmentation (a) is highlighted in blue (b). Similarly, U-Net model prediction (c) and the predictions obtained with Attention U-Net (d) are shown. The missed dense predictions by U-Net are highlighted with red arrows.

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. Each head processes the same input, but learns distinct attention weights, capturing diverse spatial relationships at once.

  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.

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**.

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

- **Study Overview:** Analyzed Attention U-Net, a recent deep learning model enhancing pancreas segmentation in CT scans via attention gates in the U-Net framework.
- **Limitation:** Results are suboptimal due to training on a reduced dataset and fewer epochs.
- **Future Scope:** Expanding dataset size and training duration could further improve performance, followed by addition of multi-head attention to introduce novelty.

References

Gibson, E., Giganti, F., Hu, Y., et al. (2017).
Automatic multi-organ segmentation with dense dilated networks.
In *MICCAI*.

Milletari, F., Navab, N., and Ahmadi, S.-A. (2016).
V-net: Fully convolutional neural networks for volumetric medical image segmentation.
In *3DV*.

Ronneberger, O., Fischer, P., and Brox, T. (2015).
U-net: Convolutional networks for biomedical image segmentation.
In *MICCAI*.

Çiçek, Ö., Abdulkadir, A., Lienkamp, S. S., Brox, T., and Ronneberger, O. (2016).
3d u-net: Learning dense volumetric segmentation from sparse annotation.
MICCAI.

Thank You