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.

Medical Image Segmentation

- It is the process of partitioning medical images — like CT scans, MRIs, or X-rays — into meaningful regions, typically to identify and delineate anatomical structures such as organs, tissues, or pathological regions.
- It plays a vital role in:
  - Disease diagnosis
  - Treatment planning
  - Quantitative analysis
- It is a specialized area within Computer Vision (CV), that focuses on teaching machines to interpret and process visual data, such as images and videos.
- Traditional segmentation methods relied on manual labeling, which were time-consuming and prone to human error.
- Deep Learning, particularly Convolutional Neural Networks (CNNs), has revolutionized this process by learning complex patterns from labeled medical images, automating feature extraction, and improving both accuracy and efficiency.

Literature Survey

1. **Çiçek et al. (2016) — 3D U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation**

- Extended U-Net for 3D medical images like CT scans, enabling volumetric segmentation across slices.
- Essential for capturing spatial relationships in pancreas segmentation tasks where inter-slice dependencies are crucial.
- Relevance: Provides a solid baseline for 3D models, directly aligning with CT-based pancreas segmentation.

Literature Survey

2. **Milletari et al. (2016) — V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation**

- Proposed V-Net, a 3D fully convolutional neural network tailored for volumetric segmentation of medical images, processing CT and MRI scans slice-by-slice.
- Introduced the Dice loss function to directly optimize segmentation accuracy, addressing class imbalance — a critical factor when segmenting small organs like the pancreas.
- Relevance: Applicable to CT-based pancreas segmentation by efficiently handling 3D medical data and overcoming imbalanced label distributions — key challenges in medical image analysis.

Literature Survey

3. **Gibson et al. (2017) — Automatic Multi-Organ Segmentation with Dense Dilated Networks**

- Proposed dense dilated convolutions to expand the receptive field without reducing spatial resolution.
- Enabled simultaneous segmentation of multiple organs — crucial for distinguishing the pancreas from neighboring structures like the liver and stomach.
- Relevance: Tackled the challenge of overlapping organs, improving the model's ability to isolate the pancreas accurately.

Literature Survey

4. **Roth et al. (2018) — Spatial Aggregation of Holistically-Nested CNNs for Pancreas Segmentation**

- Introduced Holistically-Nested CNNs (HNNs) to refine pancreas boundaries by aggregating spatial information at multiple levels.
- Focused on reducing false positives by integrating coarse-to-fine feature maps.
- Relevance: Tackled the challenge of overlapping organs, improving the model's ability to isolate the pancreas accurately.

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

Attention Gates (AGs) enable the model to automatically focus on relevant regions of an input image while suppressing irrelevant features, like background noise.

$$\mathcal{L} = \mathcal{L}_{Dice} + \mathcal{L}_{BCE}$$

1. Dice Loss Measures the overlap between the predicted segmentation $\hat{S}$ and the ground truth segmentation S:

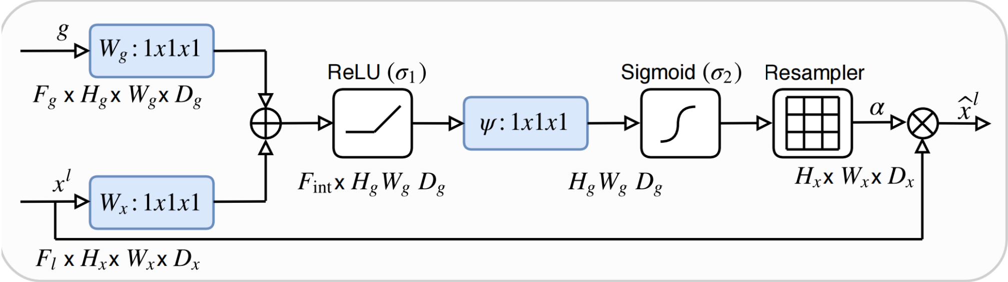
$$\mathcal{L}_{Dice} = 1 - \frac{2|S \cap \hat{S}|}{|S| + |\hat{S}|}$$

2. Binary Cross-Entropy Loss (BCE) Computes the pixel-wise difference between the true labels and predicted probabilities:

$$\mathcal{L}_{BCE} = -\sum_i \left(S_i \log(\hat{S}_i) + (1 - S_i) \log(1 - \hat{S}_i) \right)$$

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

- Data obtained from training the model on a smaller version of the **Pancreas-CT(TCIA)** dataset.
- Till now, minimal loss improvement due to limited data variation.

	A	B	C	D	E	F	G
1	Epoch	Train Seg_Loss	Validation Seg_Loss	Test Seg_Loss	Training Time (s)	Validation Time (s)	Test Time (s)
2	0	0.97	0.93	0.94	4.99	1.85	2.97
3	1	0.97	0.94	0.94	4.66	1.82	3.12
4	2	0.97	0.95	0.95	5.73	1.75	2.78
5	3	0.97	0.95	0.95	5.99	1.75	3.08
6	4	0.97	0.96	0.96	5.23	1.71	2.84
7	5	0.97	0.96	0.96	4.19	1.82	2.88
8	6	0.97	0.96	0.96	6.05	1.84	3.77
9	7	0.97	0.96	0.97	5.30	1.79	2.73
10	8	0.97	0.96	0.97	5.53	1.77	2.90
11	9	0.97	0.96	0.97	5.38	1.74	2.97
12	10	0.97	0.96	0.97	5.37	1.75	2.88
13	11	0.97	0.96	0.97	4.52	1.92	2.82
14	12	0.97	0.96	0.97	5.56	1.68	2.76
15	13	0.97	0.96	0.97	4.50	1.79	2.74
16	14	0.97	0.96	0.97	5.12	1.67	2.77

Future Improvement: Multi-Head Attention

Why: Single-head attention may miss complex patterns and global context, limiting segmentation accuracy for small, irregular structures like the pancreas.

Solution: Multi-Head Attention (MHA) splits feature maps into multiple heads, capturing diverse spatial relationships simultaneously for a richer focus.

Outcome: Enhances segmentation by improving focus on both local details and global context, seamlessly replacing single-head attention gates with MHA blocks.

Related Work: Multi-Organ Segmentation on Abdominal CT

- **Dense V-networks:** Improve feature reuse and gradient flow, enhancing segmentation accuracy, especially for small organs like the pancreas.
- **Holistically-Nested CNNs:** Capture multi-scale spatial contexts, aiding precise boundary detection in complex anatomical structures.
- **3D U-Net & V-Net:** Leverage volumetric convolutions to model 3D spatial dependencies, preserving organ continuity across CT slices.

Loss Functions: Dice Loss and Cross-Entropy Loss — optimizing the combined loss:

$$L = \lambda_1 L_{\text{Dice}} + \lambda_2 L_{\text{CE}}$$

Limitations:

- Difficulty in segmenting small, irregular structures due to insufficient focus on spatial and channel relationships.
- Lack of explicit attention mechanisms to differentiate organs with similar intensities.

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