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. **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.

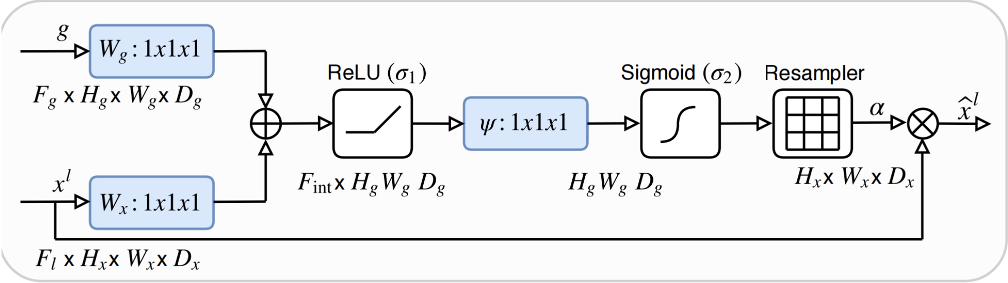
Research Focus: Attention U-Net - Learning Where to Look for the Pancreas

- **Medical Image Segmentation:** Divides medical images like CT scans into meaningful regions, identifying organs and tissues for disease diagnosis, treatment planning, and quantitative analysis. Deep Learning, particularly CNNs, automates feature extraction, boosting accuracy.
- **Attention U-Net:** Enhances pancreas segmentation by using **Attention Gates (AGs)** — mechanisms that focus on relevant regions while suppressing background noise, refining feature maps dynamically.
- **Loss Function:** Combines Dice Loss and Binary Cross-Entropy Loss (BCE) to optimize segmentation accuracy:

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

Model Architecture

Main Paper Link: click here

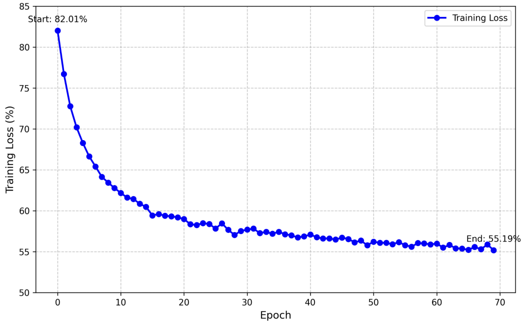


Methodology: Attention Mechanism

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(TCIA), currently trained on its reduced version
- **Number of Epochs**: 70
- **Training Time**: 41.13 s
- **Training Loss**: 55.19%
- **Overall Accuracy**: 95.3%



Future Improvement: Multi-Head Attention

- **Current Drawbacks:** The existing model relies on single-head attention, which may struggle to capture complex spatial relationships and global context, especially for small, irregular structures like the pancreas. This limits segmentation precision.
- **Proposed Solution:** Multi-Head Attention (MHA) splits feature maps into multiple attention heads, allowing the model to process diverse spatial patterns and dependencies simultaneously.
- **Impact:** MHA enhances the model's ability to focus on both fine details and broader context, leading to more accurate and robust segmentation without significantly increasing computational cost.

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:

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

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