

Abstract

In this paper, we adopt 3D Convolutional Neural Networks to segment volumetric medical images. Although deep neural networks have been proven to be very effective on many 2D vision tasks, it is still challenging to apply them to 3D tasks due to the limited amount of annotated 3D data and limited computational resources. We propose a novel 3D-based coarse-to-fine framework to *effectively* and *efficiently* tackle these challenges. The proposed 3D-based framework outperforms the 2D counterpart to a large margin since it can leverage the rich spatial information along all three axes. We conduct experiments on two datasets which include healthy and pathological pancreases respectively, and achieve the current state-of-the-art in terms of Dice-Sørensen Coefficient (DSC). On the NIH pancreas segmentation dataset, we outperform the previous best by an average of over 2%, and the worst case is improved by 7% to reach almost 70%, which indicates the reliability of our framework in clinical applications

Background

Pancreatic cancer is a major killer of human beings

- 12 out of 100,000 people have pancreatic cancer
- 330,000 new cases globally in the year of 2012 (the 7th most) [1]

Even in all types of cancer, it belongs to the most dangerous and fatal ones

- Extremely difficult to diagnose in its early stage
- In the time of diagnosis, the cancer has often spread to other organs • Most often, nothing can be done to cure the patients (5-year survival rate: 7.7% [1])

Challenges

Limited Amount of Data

- Annotation is hard and expensive
- The widely-used NIH[2] pancreas dataset has only 80 CT cases in total

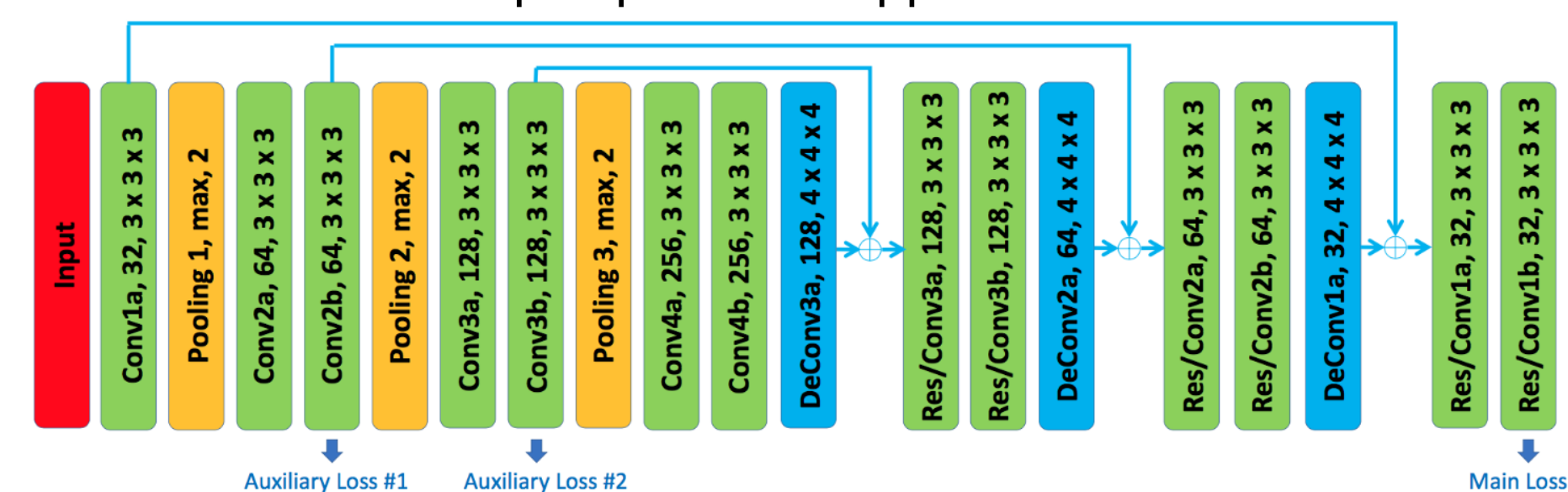
Limited Computation Resources

- Current GPUs (12GB / 16GB) cannot take a whole CT volume (512 * 512 * N) as input

Proposed Method

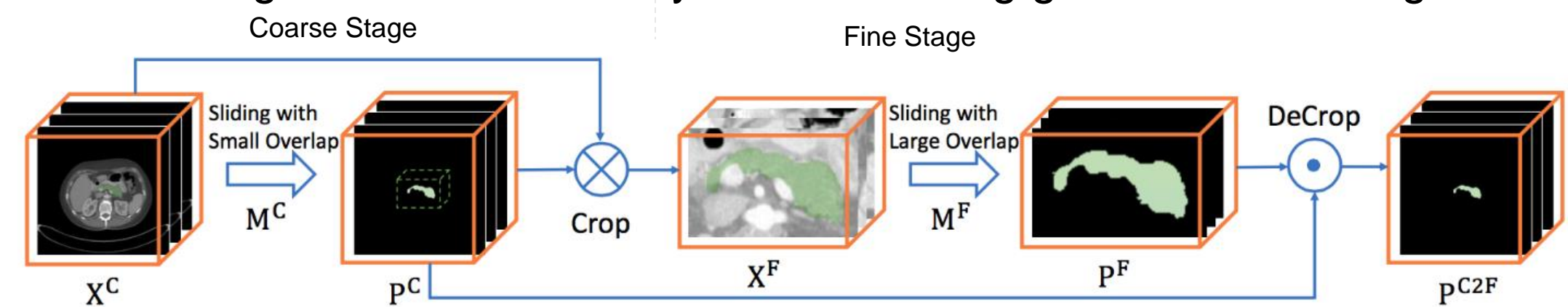
ResDSN: Patch-based Segmentation

- Encoder path followed by decoder path
- Long-term residual and deep supervision applied



Patch-based Coarse-to-Fine Segmentation

- Crop patches from CT cases to generate sufficient training samples
- Get the coarse segmentation by a coarse sliding for efficiency
- Refine the segmentation results by a dense sliding given the initial segmentation



Evaluation Matrix

- Dice-Sørensen Coefficient
 - If the set of ground-truth pancreas voxels is A and the set of predicted pancreas voxels is B , then the accuracy of segmentation, or the Dice-Sørensen coefficient (DSC), is computed as $2 \times |A \cap B| / (|A| + |B|)$
- DSC = $\frac{2 \times 10}{20 + 19} = 51.28\%$
- Ground-truth (20 voxels)
 - Prediction (19 voxels)
 - Overlap (10 voxels)

Ablation Study

Time Cost

Method	Mean DSC	n	Testing Time (s)
ResDSN C2F (Ours)	84.59 ± 4.86%	6&12	245
ResDSN Coarse (Ours)	83.18 ± 6.02%	6	111
ResDSN Fine (Ours)	83.96 ± 5.65%	12	382

Table 5. Average time cost in the testing phase, where n controls the overlap size of sliding windows during the inference.

Residual Connection

Method	Mean DSC	Max DSC	Min DSC
ResDSN Coarse (Ours)	83.18 ± 6.02%	91.33%	58.44%
FResDSN Coarse	83.11 ± 6.53%	91.34%	61.97%
SResDSN Coarse	82.82 ± 5.97%	90.33%	62.43%
DSN [6] Coarse	82.25 ± 5.91%	90.32%	62.53%

Table 4. Evaluation of different residual connections on NIH.

Deep Supervision

Method	Mean DSC	Max DSC	Min DSC
ResDSN C2F (Ours)	84.59 ± 4.86%	91.45%	69.62%
Res C2F	84.06 ± 6.51%	91.72%	51.83%

Table 6. Discussions of the deep supervision on NIH.

Results

Table 2. Evaluation of different methods on the NIH pancreas dataset[2]. Our proposed framework achieves the state-of-the-art by a large margin compared with previous state-of-the-arts.

	DSC	C2F (Ours)	Coarse (Ours)	Cai et al[4]	Zhou et al[7]	Dou et al[6]	Roth et al[5]	Yu et al[9]	Roth et al[2]
Average		84.59±4.86	83.18±6.02	82.40±6.70	82.37±5.68	82.25±5.91	78.01±8.20	71.96±15.34	71.42±10.11
Max		91.45	91.33	90.10	90.85	90.32	88.65	89.27	86.29
Min		69.42	58.44	60.00	62.43	62.53	34.11	0	23.99

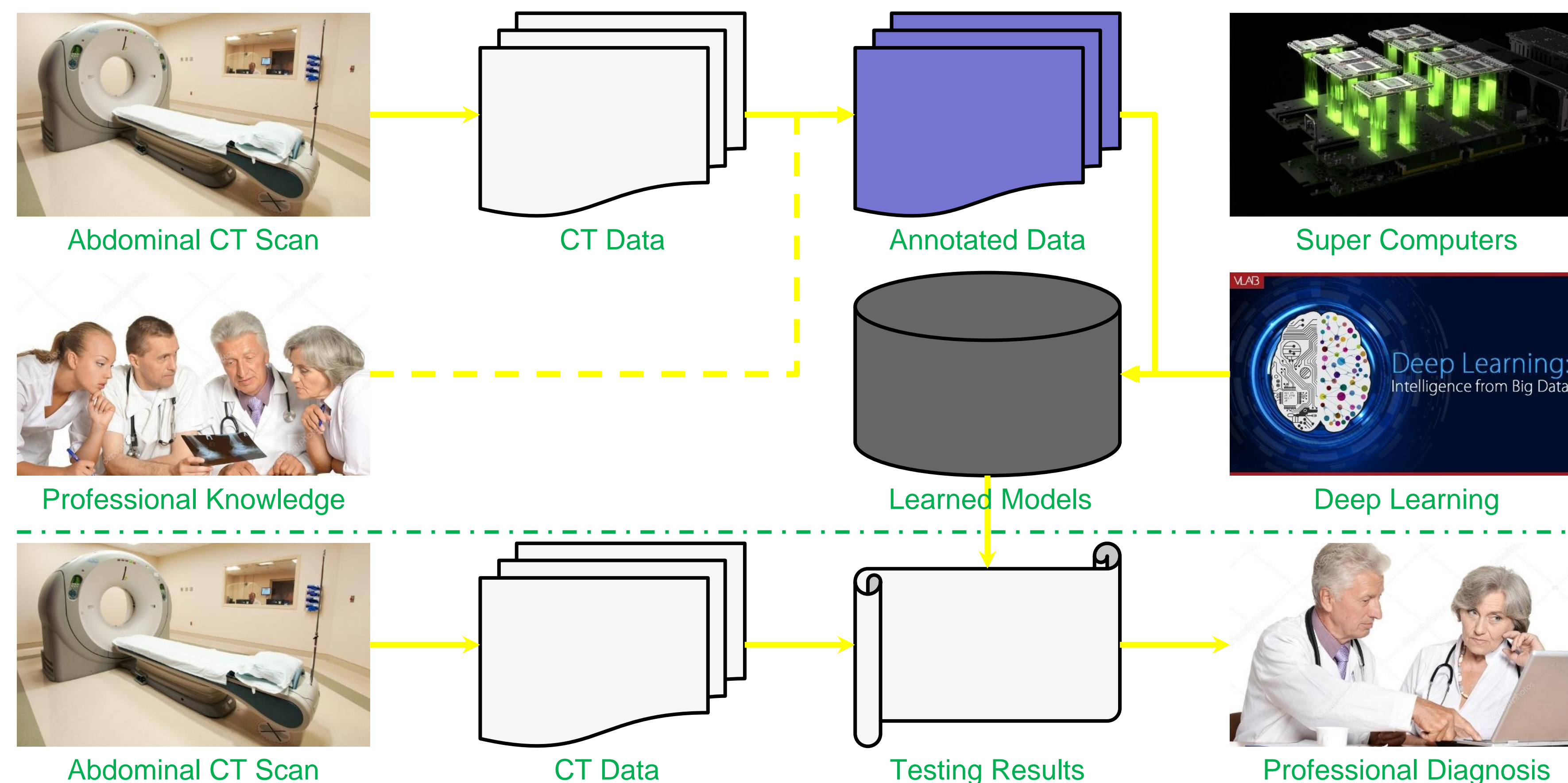
Table 3. Evaluations of the JHMI pathological pancreas dataset[3].

	DSC	C2F (Ours)	Coarse (Ours)	Zhou et al[33]
Average		80.56±13.36	77.96±13.36	79.23±9.72
Max		93.82	93.23	92.95
Min		18.61	16.72	34.65

Figure 4. Examples of segmentation results reported by “ResDSN Coarse” and “ResDSN C2F” on a same slice in the axial view from NIH case #33, #63 and #74, respectively. Numbers after “Coarse” or “C2F” mean testing DSC. Red, green and yellow indicate the ground truth, prediction and overlapped regions, respectively.



Workflow



Ongoing[8]

- Technical report available [8]
- Pancreatic Ductal Adenocarcinoma – the most common pancreatic cancer
- Classification of the PDAC cases from CT scans
- 303 normal cases and 136 abnormal cases (diagnosed as PDAC)
- A sensitivity of 94.1% at a specificity of 98.5%

References

References in this poster are enumerated of their presences in this poster, not same with the paper.

- [1] Stewart, B.W.K.P., Wild, C.P., et al.: World cancer report 2014. Health
- [2] H. R. Roth, L. Lu, A. Farag, H.-C. Shin, J. Liu, E. B. Turkbey, and R. M. Summers. Deeporgan: Multi-level deep convolutional networks for automated pancreas segmentation. In MICCAI, 2015.
- [3] Y. Zhou, L. Xie, E. K. Fishman, and A. L. Yuille. Deep supervision for pancreatic cyst segmentation in abdominal CT scans. In MICCAI, 2017.
- [4] J. Cai, L. Lu, Y. Xie, F. Xing, and L. Yang. Improving deep pancreas segmentation in CT and MRI images via recurrent neural contextual learning and direct loss function. 2017.
- [5] H. R. Roth, L. Lu, A. Farag, A. Sohn, and R. M. Summers. Spatial aggregation of holistically-nested networks for automated pancreas segmentation. In MICCAI, 2016.
- [6] Q. Dou, L. Yu, H. Chen, Y. Jin, X. Yang, J. Qin, and P.-A. Heng. 3D deeply supervised network for automated segmentation of volumetric medical images. MIA, 41:40–54, 2017.
- [7] Y. Zhou, L. Xie, W. Shen, Y. Wang, E. K. Fishman, and A. L. Yuille. A fixed-point model for pancreas segmentation in abdominal CT scans. In MICCAI, 2017.
- [8] Zhu, Z., Xia, Y., Xie, L., Fishman, E.K. and Yuille, A.L., 2018. Multi-Scale Coarse-to-Fine Segmentation for Screening Pancreatic Ductal Adenocarcinoma. arXiv preprint arXiv:1807.02941.
- [9] L. Yu, J.-Z. Cheng, Q. Dou, X. Yang, H. Chen, J. Qin, and P.-A. Heng. Automatic 3D cardiovascular MR segmentation with densely-connected volumetric convnets. In MICCAI, 2017.

Acknowledgements

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