Joint Liver Lesion Segmentation and Classification via Transfer Learning

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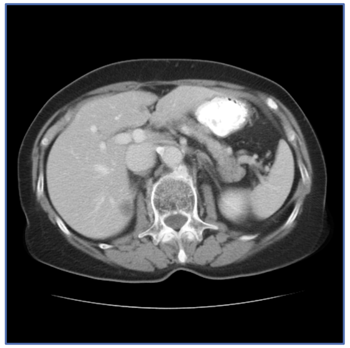
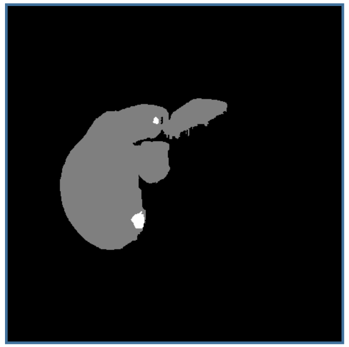
Introduction: Lesion segmentation & classification





Lesion class

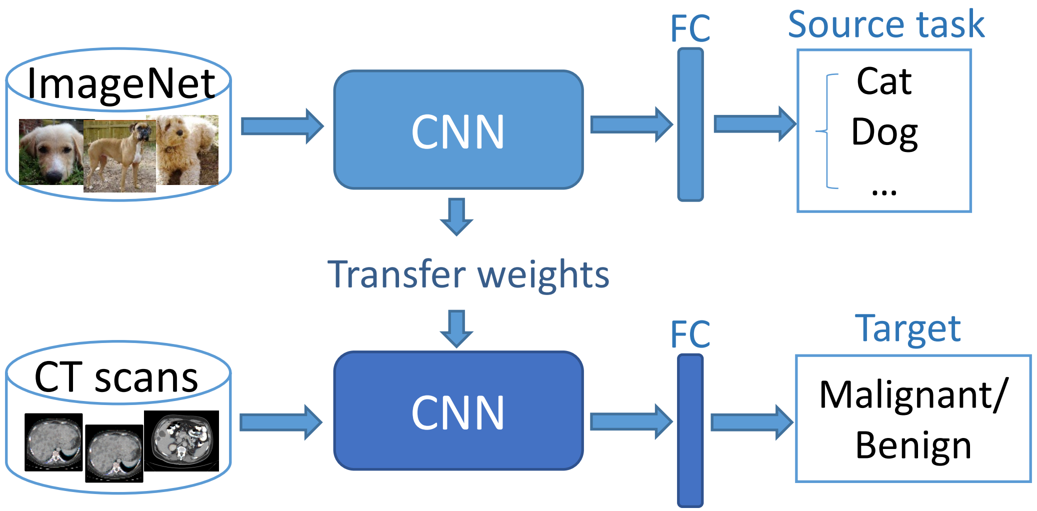
- Liver lesion segmentation has attracted attention in recent years, with publicly available datasets that enable comparison between different methods.
- In practice, it is also important to separate between malignant and benign lesions by classifying detected lesions.
- **Liver lesion classification is far less investigated with very limited-sized datasets explored and no public data available.**

➢ We focus on **classification** of liver CT images that include both benign and malignant lesions.

Introduction: Main challenge

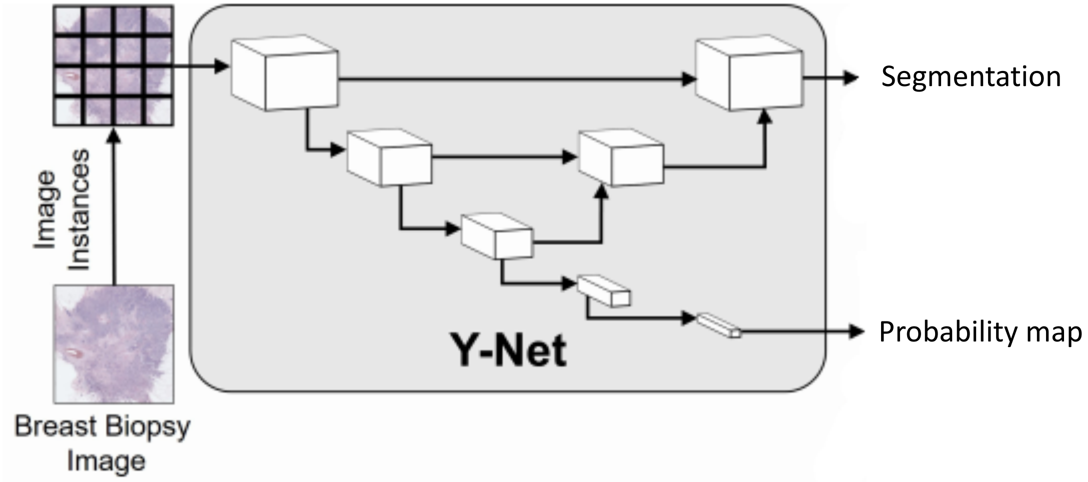
- The lack of sufficient amounts of annotated data is one of the main challenges in the medical imaging domain.

1) **Transfer learning**



- Transfer learning has been proven to have better performance when the tasks of the source and target network are similar [1].

2) **Joint learning**



- Adding an additional branch for classification results in improved segmentation performance [2].

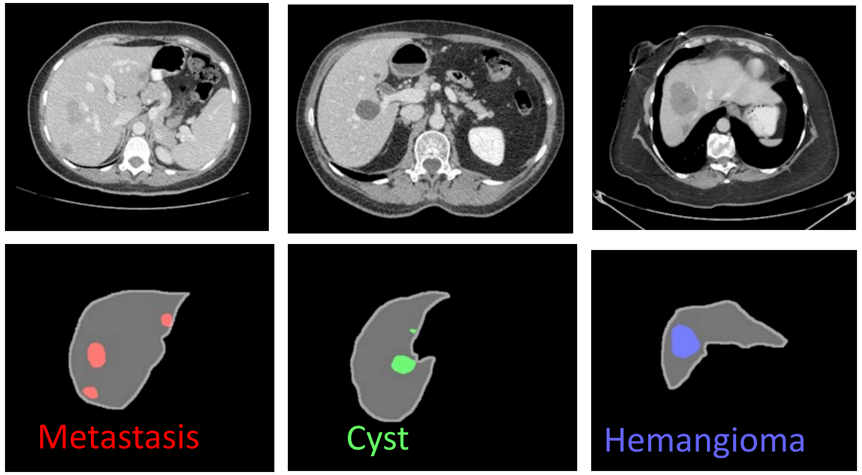
[1] Mohammad Hesam Hesamian, Wenjing Jia, Xiangjian He, and Paul Kennedy. Deep learningtechniques for medical image segmentation: Achievements and challenges.Journal of digitalimaging, 32(4):582–596, 2019

[2] Mehta, Sachin, et al. "Y-Net: joint segmentation and classification for diagnosis of breast biopsy images." *International Conference on Medical Image Computing and Computer Intervention*. Springer, Cham, 2018.

Data

Sheba dataset

- <u>332 2D CT slices</u> taken from 140 patients.
- Annotations of:
  - *liver segmentation*
  - *lesion segmentation*
  - *lesion classification* into 3 classes: **cyst, hemangioma, metastasis**

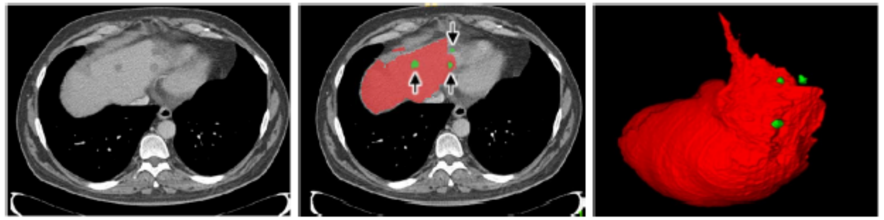


* Private dataset

LiTS dataset (Liver Tumor Segmentation)

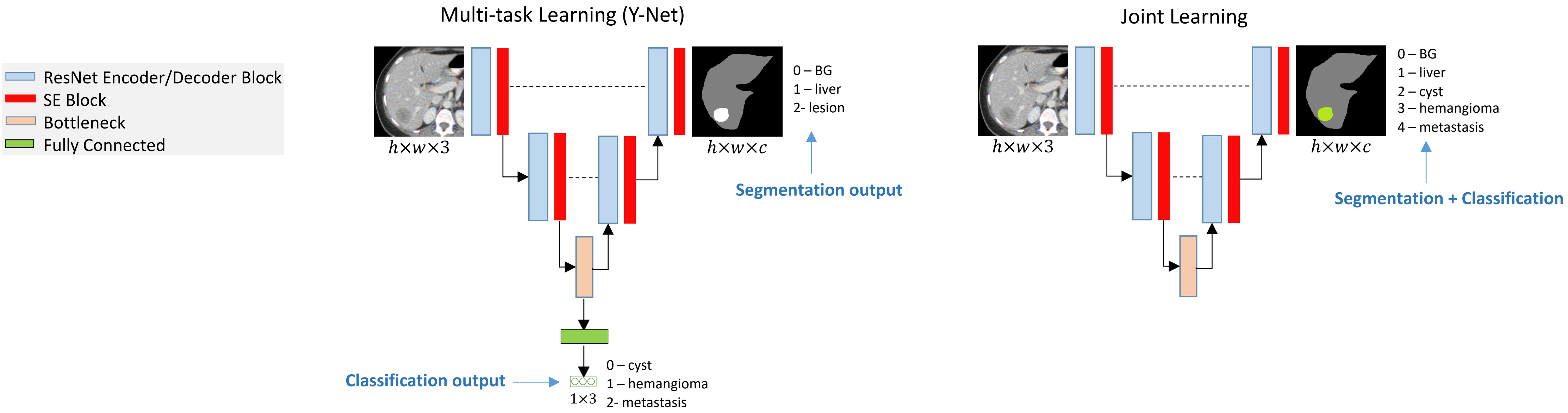
- 130 3D CT <u>scans</u> (~<u>60,000 2D CT slices</u>).
- Annotations of:
  - *liver segmentation*
  - *lesion segmentation*

ISBI 2017



* Publicly available dataset

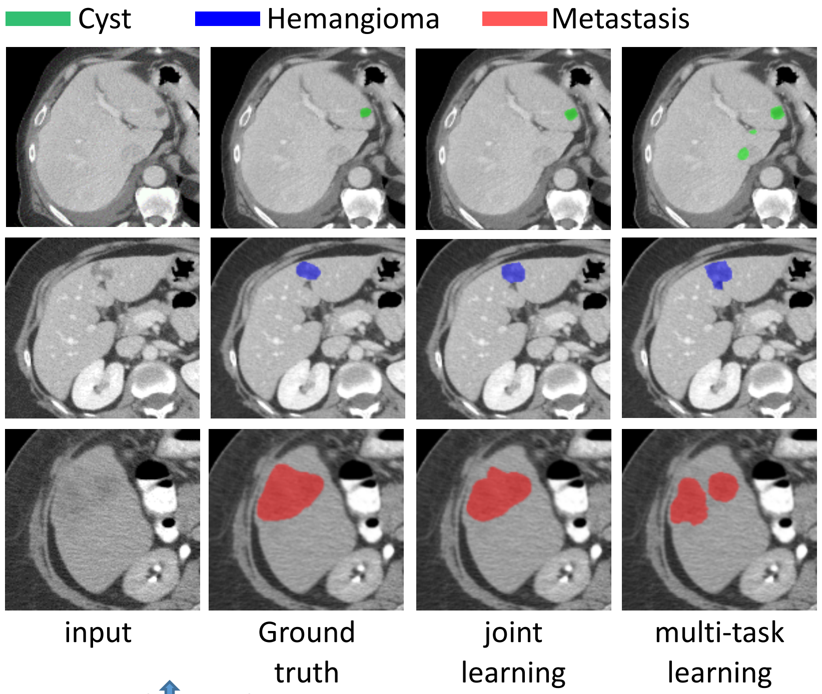
Methods: The proposed frameworks



- We perform fine-tuning with different weights initialization:
  1) Training from scratch (random initialization).
  2) Fine-tuning with ImageNet weights
  3) Fine-tuning with LiTS weights (self-trained lesion segmentation model). ← **Same domain!**

Results & Conclusions

Training strategy	Fine-tuning	Cls Acc	Seg Dice	Seg Recall
1. Classification baseline	**scratch**	0.55	-	-
	ImageNet	0.63	-	-
	LiTS	0.76	-	-
2. Segmentation baseline	**scratch**	-	0.59	0.59
	ImageNet	-	0.63	0.67
	LiTS	-	0.71	0.72
3. Multi-task learning (Y-Net)	**scratch**	0.43	0.49	0.43
	ImageNet	0.68	0.67	0.65
	LiTS	0.79	0.71	0.68
4. Joint learning	**scratch**	0.63	0.57	0.60
	ImageNet	0.74	0.64	0.70
	LiTS	**0.86**	**0.71**	**0.76**



- ✓ The simple joint framework outperforms the commonly used multi-task architecture (↑7%).
- ✓ Pretraind with LiTS better than imageNet (↑12%).

- ➢ Joint network classification and localization context are shared for mutual benefit.
- ➢ Pre-training the network with data from the same domain improves feature learning and generalization.