A Normalized Fully Convolutional Approach to Head and Neck Cancer Outcome Prediction

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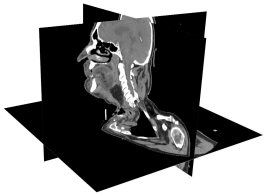
Treatment context and medical imaging data

Diagnosis
FDG PET-CT

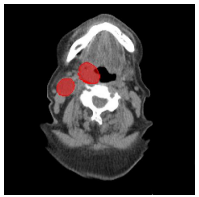
Planning
Planning CT

Treatment
(Chemo-)Radiotherapy

Follow-up
43 months (6-112)



298 H&N cancer patients



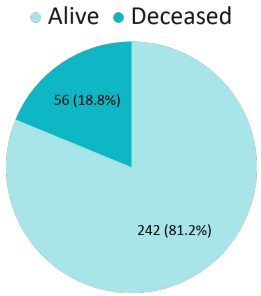
Preprocessing

- 3D → 2d using max GTV area
- Isotropic resampling to 1×1 mm
- Resizing to 128×128
- Normalizing PET to SUV

Data Augmentation (x20)

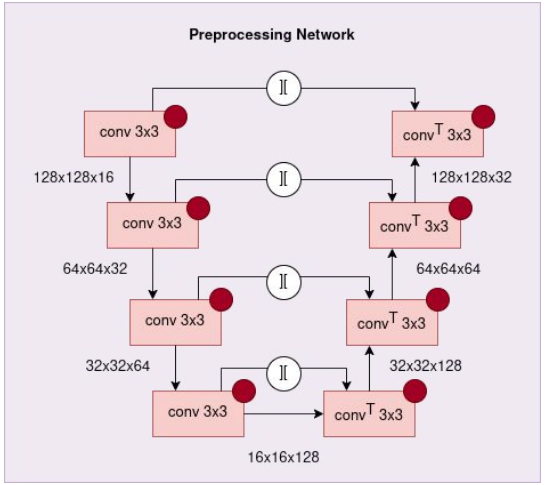
- Flip 50% probability
- Shift up to 40%
- Rotate up to 20 degrees

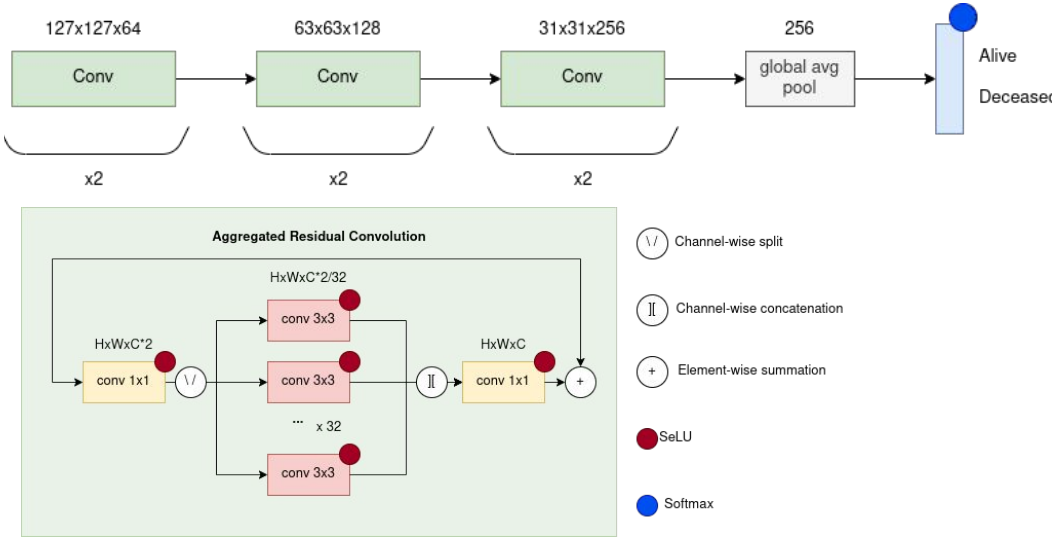
Deep Convolutional Neural Network



[1] Vallières, M, et al. (2017). Data from Head-Neck-PET-CT. The Cancer Imaging Archive.

Proposed model





[1] Xie, Saining, et al. "Aggregated residual transformations for deep neural networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*, 1492-1500 (2017).

[2] Drozdzal, M. *et al*. Learning normalized inputs for iterative estimation in medical image segmentation. *Med. image analysis* 44, 1–13 (2018).

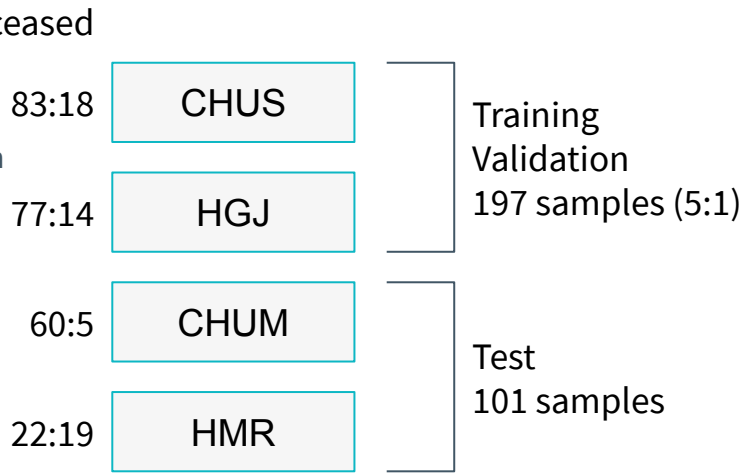
Training and Evaluation

Characteristics

- SeLU activation as regularizer/normalization
- Residual connections to improve convergence rate
- Aggregated convolutions for model capacity regularization
- FCN as an target-oriented image-to-image domain translation or image normalizer

Implementation

- PyTorch using GeForce RTX 2080 TI
- Categorical cross-entropy loss
- 1:8 resampling to combat data imbalance
- Adam optimizer: 0.0006 lr
- Batch size: 8
- Dataset augmented 20 times
- Total epochs: 100 (1 hour)



[1] Vallières, M. et al. Radiomics strategies for risk assessment of tumour failure in head-and-neck cancer. *Sci Rep* 7, 10117 (2017).

Survival binary classification prediction results

AUC (Spec, Sens)	PET	CT	Masked CT	PET-CT	
CNN[1]	**59%** (90%, 29%)	57% (37%, 77%)	*67%* (82%, 52%)	65% (99%, 30%)	930,146 parameters
FCN+CNN	**59%** (41%, 77%)	65% (51%, 79%)	63% (35%, 90%)	*70%* (69%, 71%)	1,321,682 parameters
AggResCNN	50% (100%, 0%)	65% (54%, 76%)	**69%** (51%, 87%)	*74%* (66%, 82%)	291,874 parameters
FCN+AggResCNN (ours)	57% (21%, 94%)	**70%** (46%, 94%)	67% (52%, 82%)	***76%*** (61%, 91%)	683,650 parameters

[1] Diamant, A., Chatterjee, A., Vallières, M., Shenouda, G. & Seuntjens, J. Deep learning in head & neck cancer outcome prediction. *Sci. reports* 9, 1–10 (2019).

Conclusion

1. Our proposed CNN model improves over the state-of-the-art for head and neck cancer survival outcome prediction (76% > 65%).
2. Incorporating PET imaging information improves model performance.
3. Our proposed architectural change (FCN, aggregated residual connections) benefit model performance without incurring a larger model complexity cost.
4. The addition of the FCN improves performance when coupled with more complex input features (CT, PET-CT).