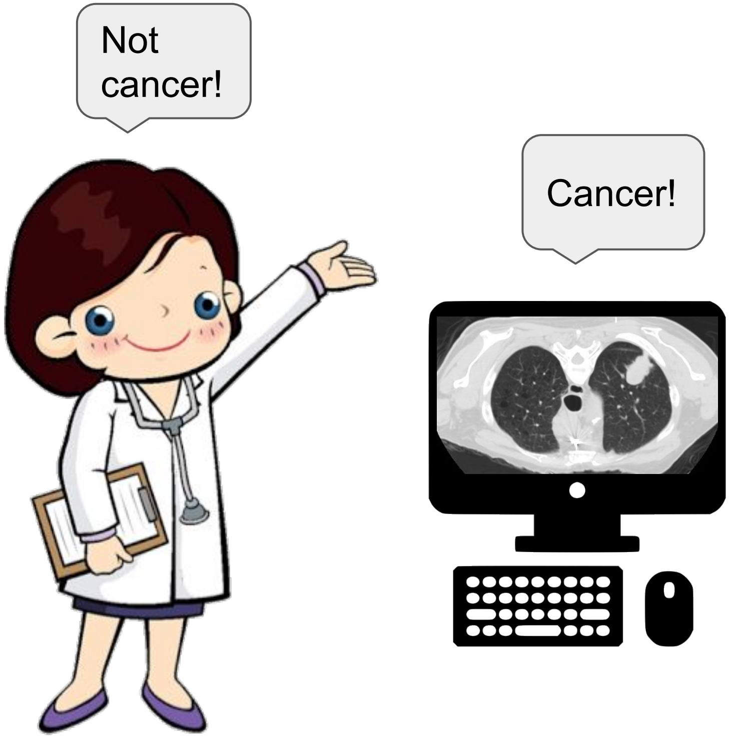
A Case Study of Transfer of Lesion Knowledge

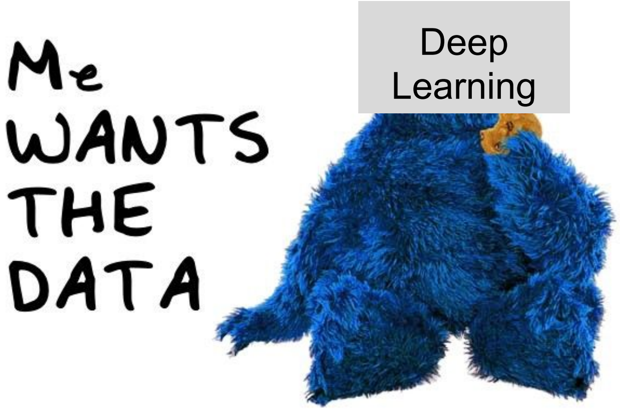
Motivation

- Cancer is one of the deadliest diseases, with plenty of people commonly misdiagnosed
- CAD is important as a second opinion
- Deep models are very good with image data



Motivation

- Deep models require a lot of data
- Access to large-scale medical data is a problem:
  - Privacy concerns around sharing medical data
  - Getting annotations is costly
  - Some organs have lesser data than others, makes making CAD systems for organs with sparse data tougher

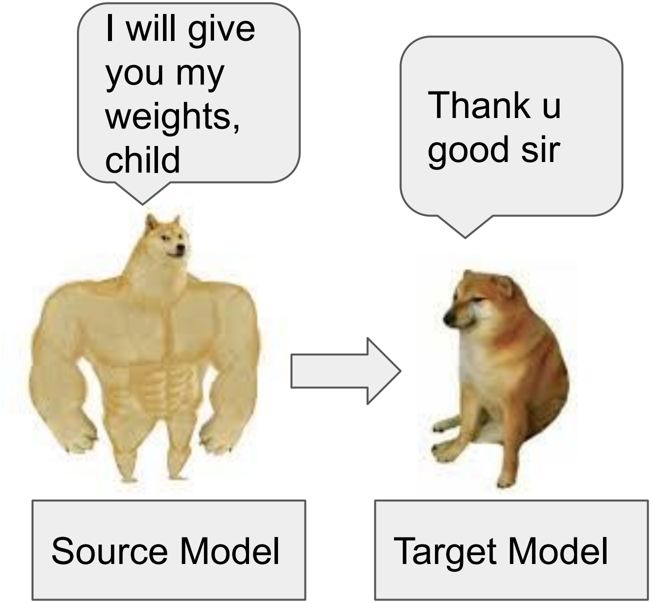


Solution- Transfer learning

- Transfer learning- method for dealing with lack of data. Transfer weights from a model with more data to to that with lesser data

- Standard way- Imagenet weights

- Can we do better????

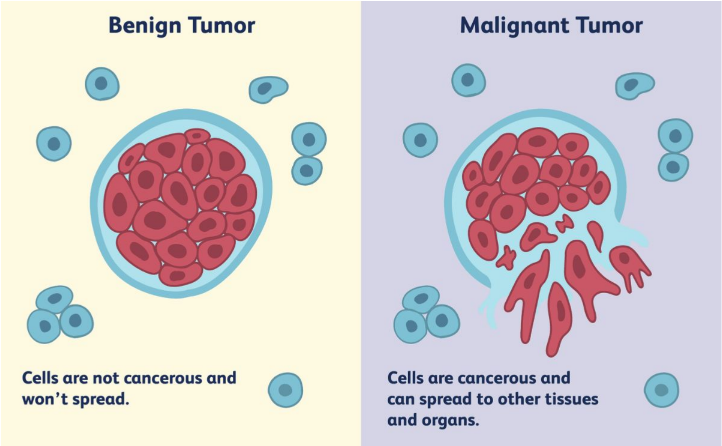


He, K., Girshick, R., Doll´ar, P.: Rethinking imagenet pre-training (2018)

Case for lesion-specific models

Benign Tumours

- Sharp margins
- No enhancing rim
- Homogenous gradient



Malignant Tumours

- Irregular boundaries
- Thickening at the periphery
- Non-smooth gradient

Image from https://www.verywellhealth.com/what-does-malignant-and-benign-mean-514240

Methodology

BASELINE Model

Source- NA
Target- Organ

LESION-AGNOSTIC Model
Source- Imagenet
Target- Organ

LESION-AUGMENTED Model
Source- Organ
Target- Organ

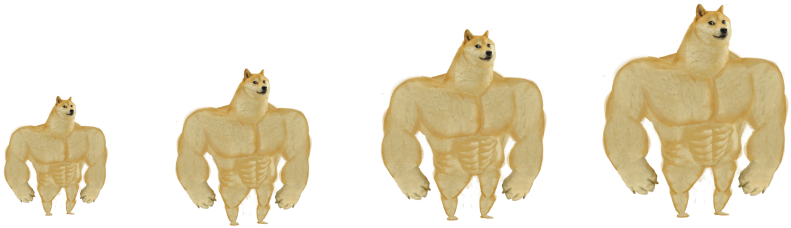
Methodology

LESION-AUGMENTED Model
Source- Organ
Target- Organ

Source Data size constant

Target Data size constant

Source Data- Constant



V. Low | Low | Medium | High

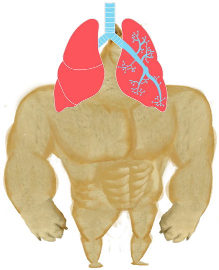
Target Data

Target Data- Constant

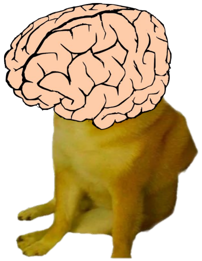
V. Low | Low | Medium | High

Source Data

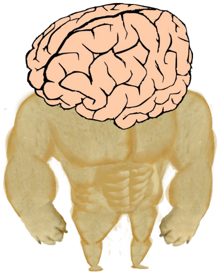
Methodology



Source



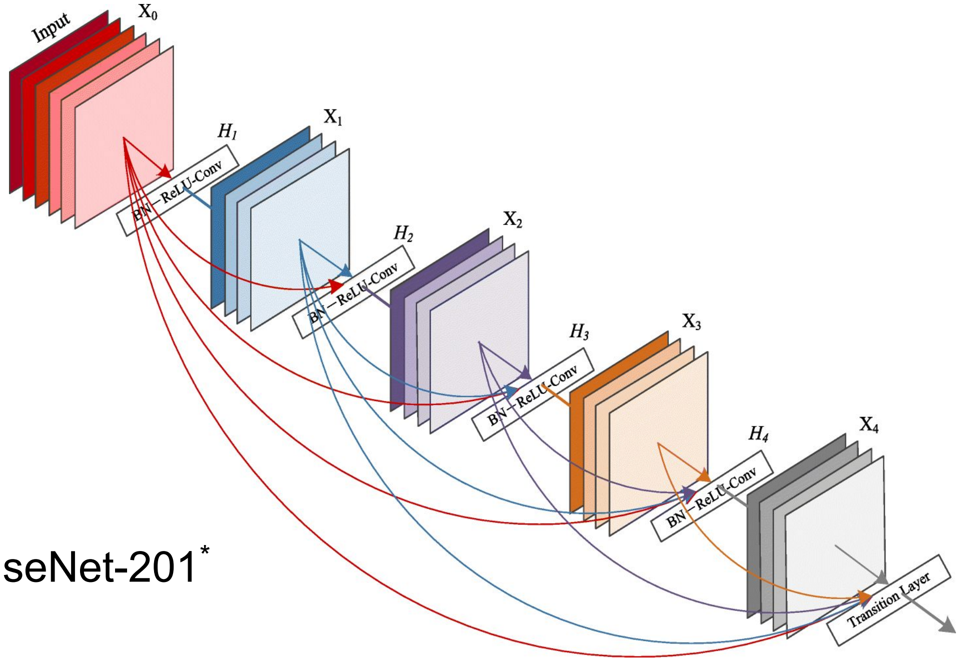
Target



Source

Target

Network Architecture

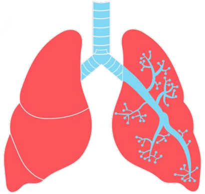


DenseNet-201*

- Adam Optimiser
- Binary Cross Entropy Loss
- Learning Rate : 1e-4
- Batch Size : 64

* Image from https://pytorch.org/hub/pytorch_vision_densenet/

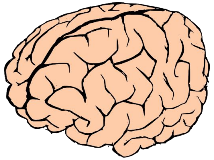
Datasets



LIDC-IDRI

- Diagnostic and lung cancer screening thoracic CT scans with marked-up annotated lesions
- Malignancy values from 1 to 3 were considered as benign, and the rest were considered malignant.

Clark, K. et al. : The cancer imaging archive (tcia): Maintaining and operating a public information repository. https://doi.org/10.1007/s10278-013-9622-7



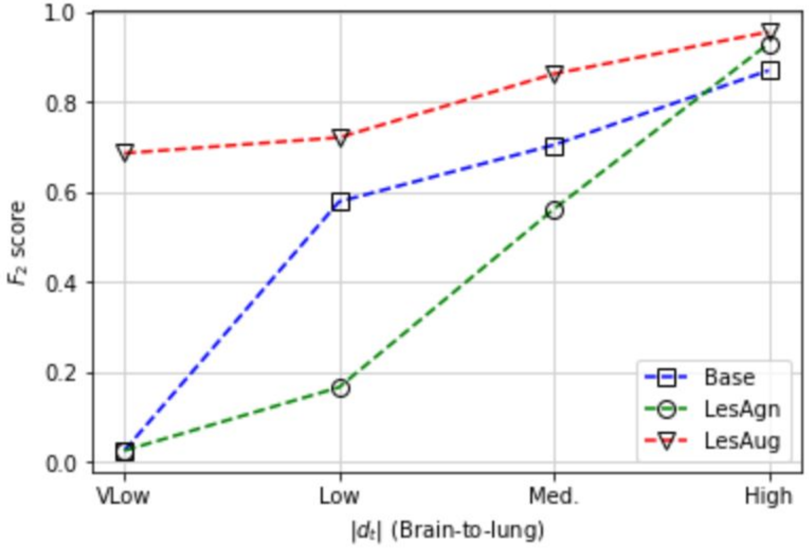
Brain Tumour Dataset

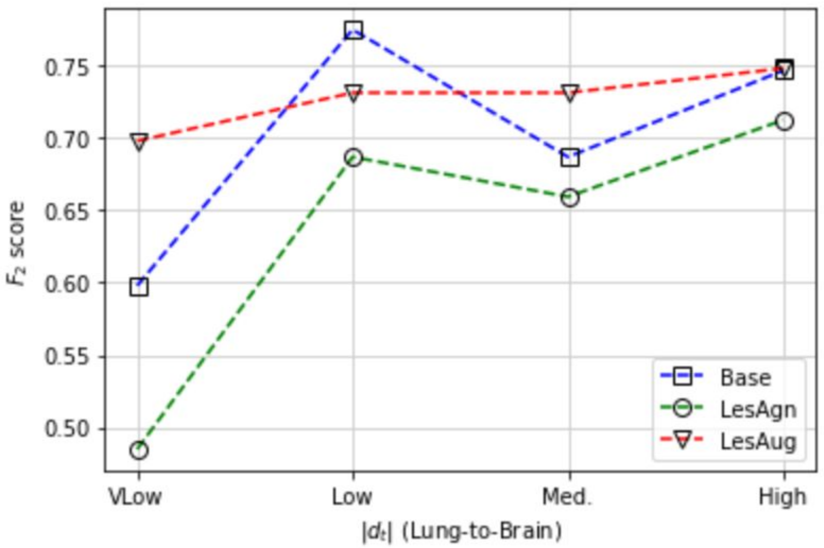
- Weighted contrast-enhanced images from patients with meningioma, glioma and pituitary tumours
- Meningioma and Pituitary tumours were taken as benign, and glioma tumours were taken as malignant.

Cheng, J.: brain tumor dataset (April 2017), https://figshare.com/articles/dataset/brain_tumor_dataset/1512427

Results

1. Given enough source training data, target models obtained using lesion-augmented transfer perform better than those obtained using lesion agnostic transfer

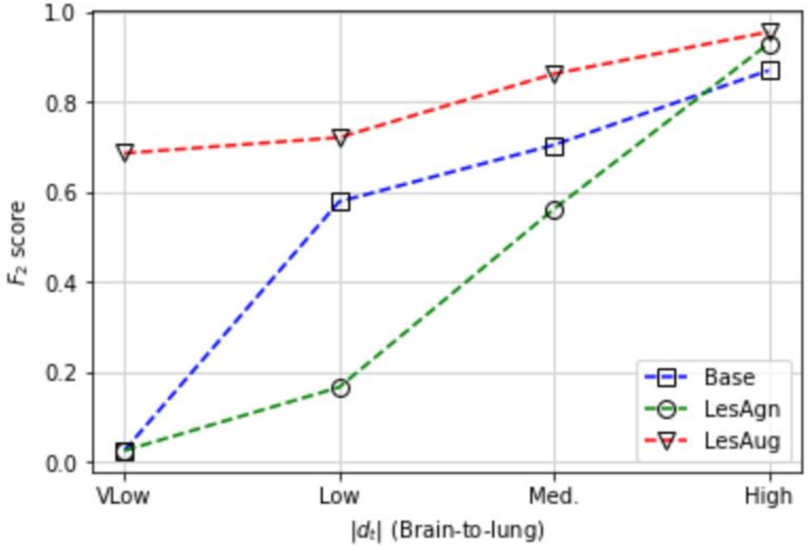


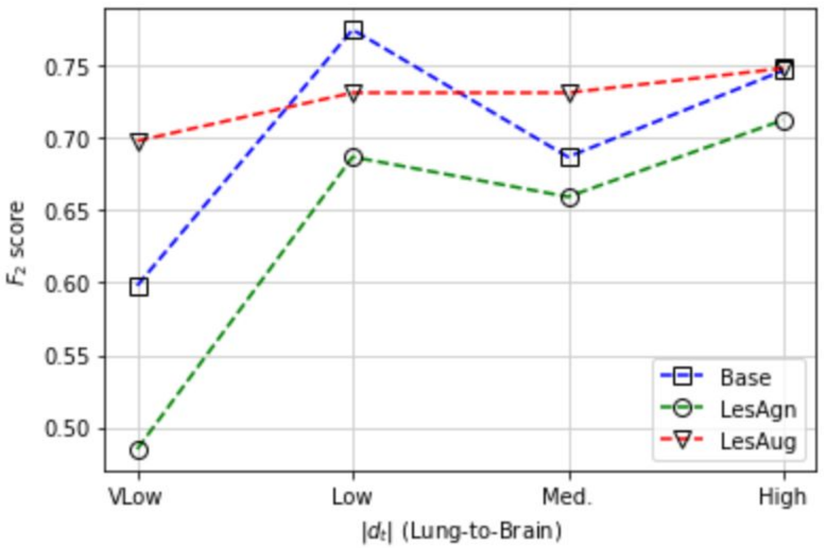


Inclusion of 5000 (or fewer) lesion-specific source images gives better performance than over 15M lesion-agnostic source images

Results

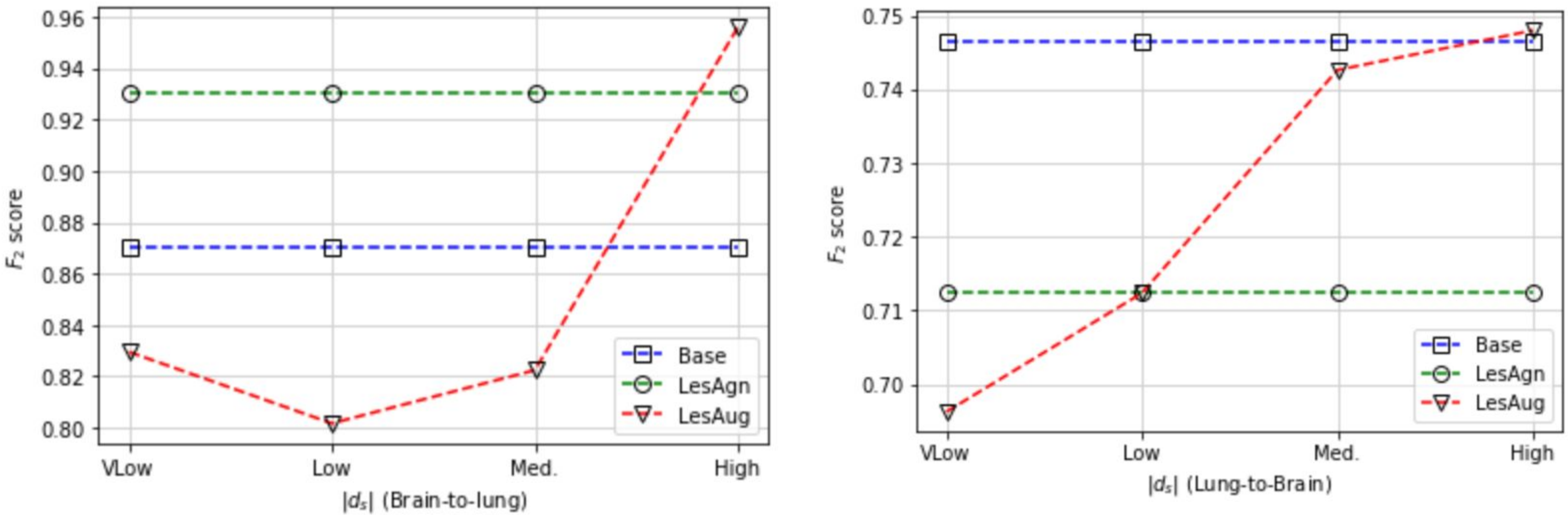
2. As the lesion augmented target data size (d_t) decreases, the benefit of lesion-augmented transfer over lesion-agnostic transfer increases





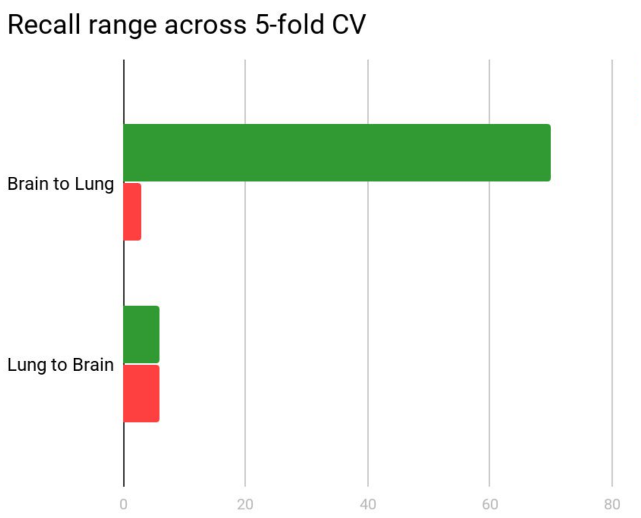
Results

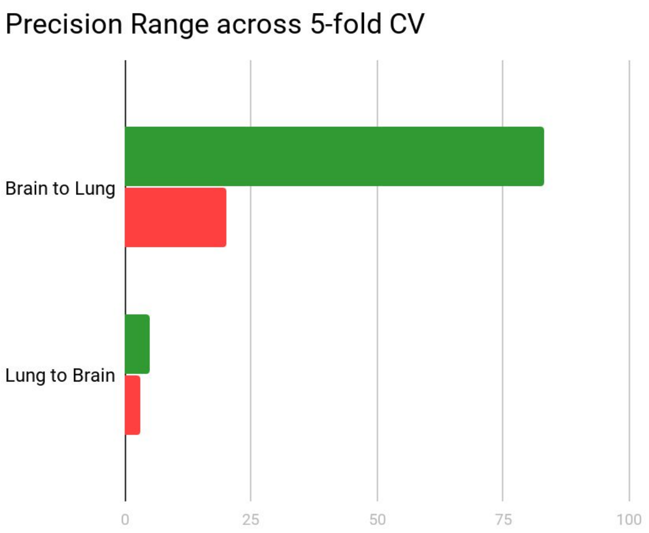
3. As the source data size (d_s) decreases, the lesion-augmented models get less effective



Results

4. Lower Variance of Lesion-Augmented Models





Results

5. Faster Convergence of Lesion-Augmented models:

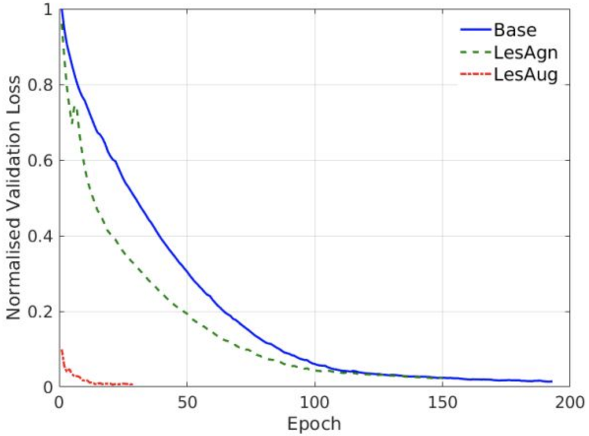
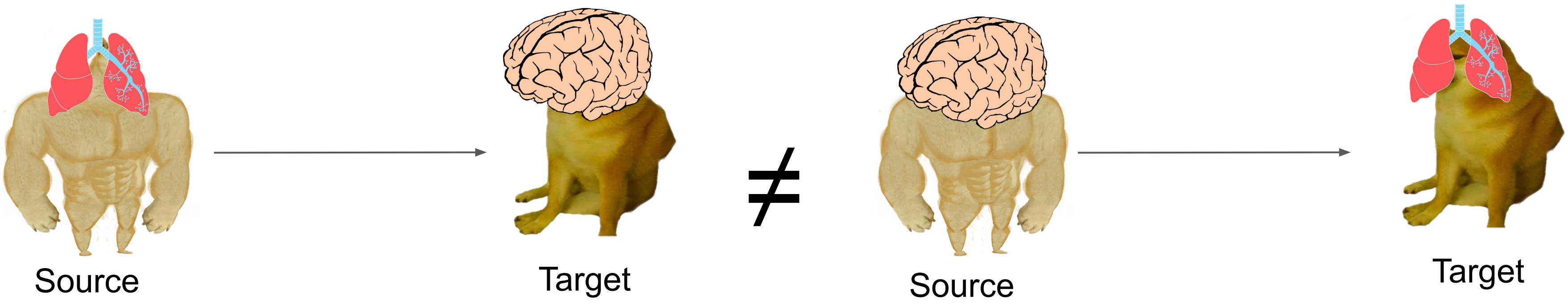


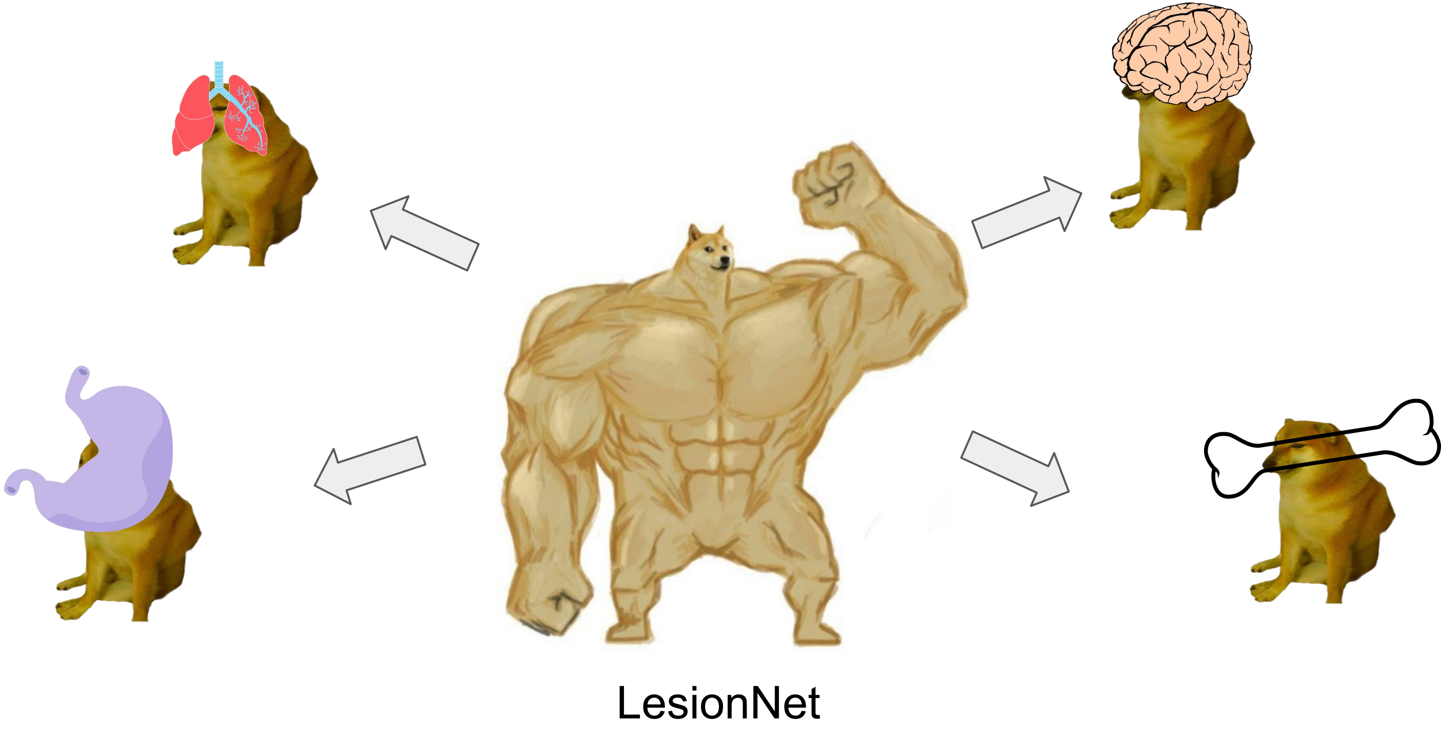
Fig. 5. Loss vs epochs for brain-to-lung transfer, using a “VLow” value of $|d_t|$

Future Scope



Why?

Future Scope



Yan, K., Wang, X., Lu, L., Summers, R.: Deeplesion: Automated mining of large scale lesion annotations and universal lesion detection with deep learning. Journal of Medical Imaging 5, 1 (07 2018). https://doi.org/10.1117/1.JMI.5.3.036501

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