Lung Cancer Segmentation

Deep Neural Networks Final Project

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Research Statement

Comparative Analysis on Multiple
Methods to Identify and Segment Lung
Cancer Tumors

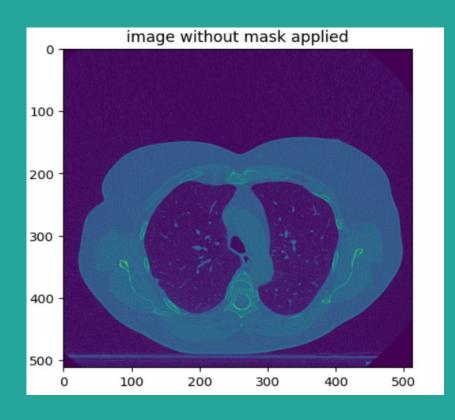
Agenda

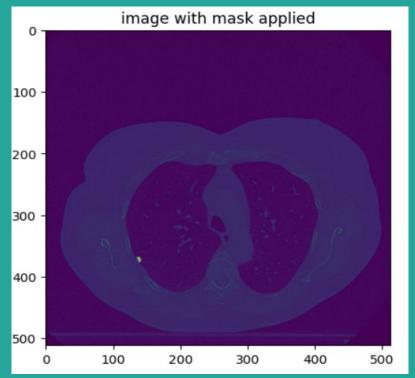
- Dataset Overview
- Model 1: NN for per-pixel classification (semantic segmentation)
- Model 2 & 3: 2D convolution per slice instance segmentation
- Model 4: 3D convolution per voxel instance segmentation

Dataset

- The training set consisted of 708 CT images and the test set contained 264 CT images.
- Approximately 30 training lungs and 10 test lungs.
- This dataset is a fusion of original Kazakhstani local data from the Kazakh Research Institute of Oncology and Radiology

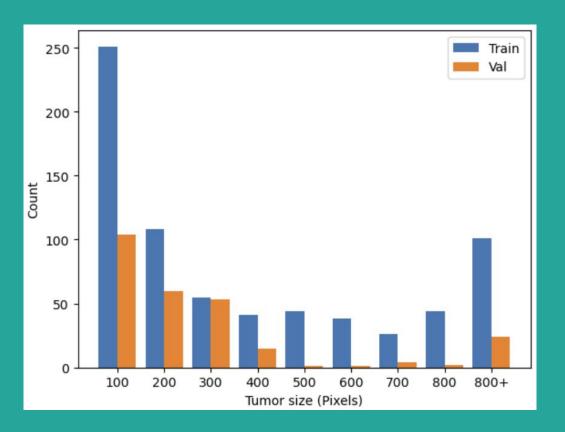
Dataset: Sample Images



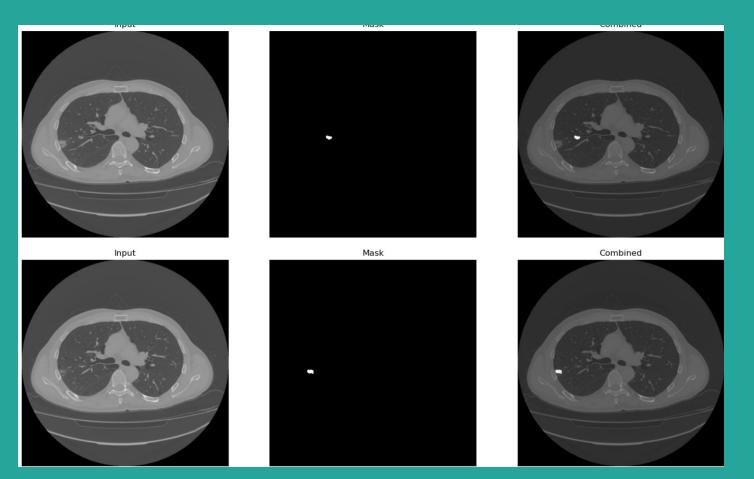


Dataset: Distribution

262144 total pixels of dimensions 512x512

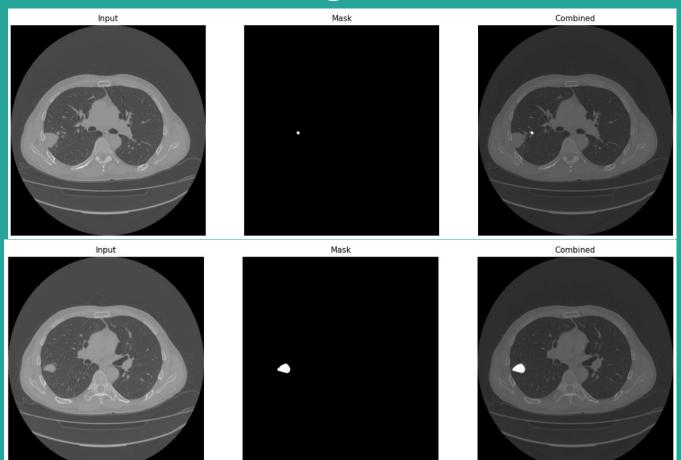


Dataset: Incorrect Data



Data represented is supposed be a contiguous slice but has changing locations.

Dataset: Confusing Data



Data represented is supposed be a contiguous slice but has varying size and shape.

Related Work

	BTCV n=30	ACDC n=200	LiTS n=131	BraTS n=1251		AMOS n=360
nnU-Net (org.) [21]	83.08	91.54	80.09	91.24	86.04	88.64
nnU-Net ResEnc M	83.31	91.99	80.75	91.26	86.79	88.77
nnU-Net ResEnc L	83.35	91.69	81.60	91.13	88.17	89.41
nnU-Net ResEnc XL	83.28	91.48	81.19	91.18	88.67	89.68
MedNeXt L k3 [31]	84.70	92.65 92.62	82.14	91.35	88.25	89.62
MedNeXt L k5 [31]	85.04		82.34	91.50	87.74	89.73
STU-Net S [20]	82.92	91.04	78.50	90.55	84.93	88.08
STU-Net B [20]	83.05	91.30	79.19	90.85	86.32	88.46
STU-Net L [20]	83.36	91.31	80.31	91.26	85.84	89.34
SwinUNETR [32]	78.89	91.29	76.50	90.68	81.27	83.81
SwinUNETRV2 [17]	80.85	92.01	77.85	90.74	84.14	86.24
nnFormer [41]	80.86	92.40	77.40	90.22	75.85	81.55
CoTr [37]	81.95	90.56	79.10	90.73	84.59	88.02
No-Mamba Base	83.69	91.89	80.57	91.26	85.98	89.04
U-Mamba Bot [26]	83.51	91.79	80.40	91.26	86.22	89.13
U-Mamba Enc [26]	82.41	91.22	80.27	90.91	86.34	88.38
A3DS SegResNet [1,28]	80.69	90.69	79.28	90.79	81.11	87.27
A3DS DiNTS [1,18]	78.18	82.97	69.05	87.75	65.28	82.35
A3DS SwinUNETR [1,32]	76.54	82.68	68.59	89.90	52.82	85.05

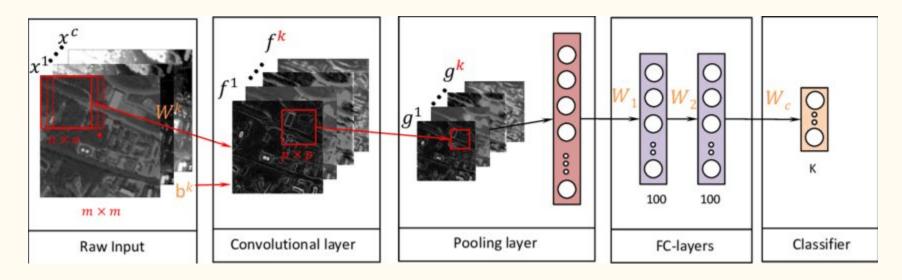
Past research in this field yields a Dice Score of 80-90%

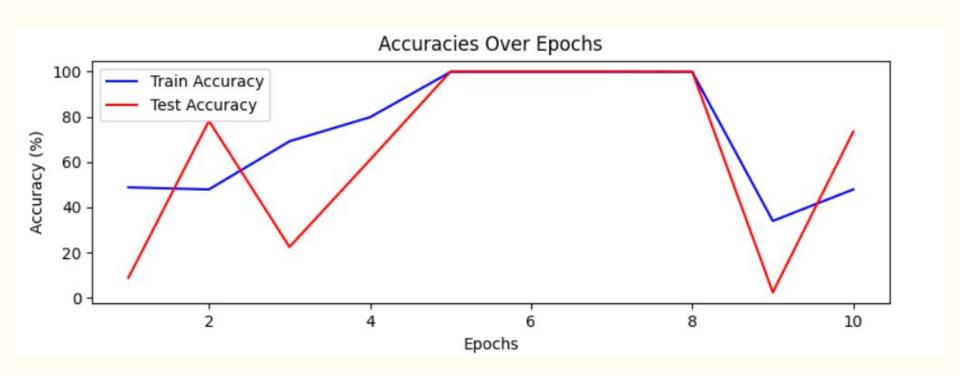
Rows represent different models, Columns represent different datasets tested

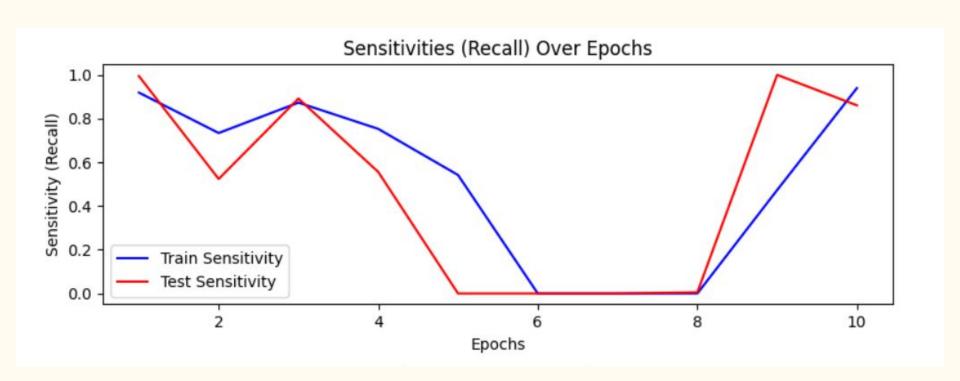
Table 1. Benchmark results of prevalent 3D medical segmentation methods measured as DSC score [%].

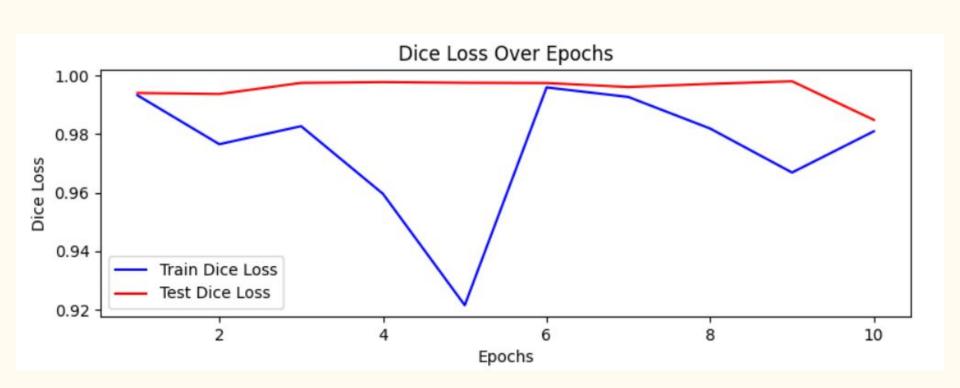
Baseline Simple Model

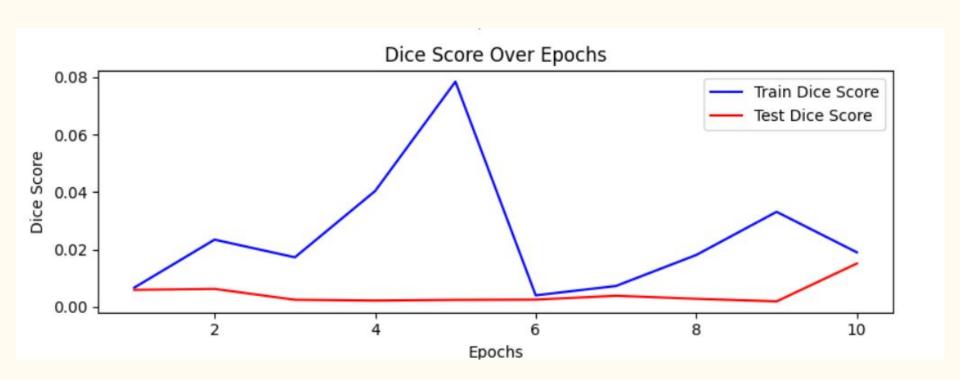
• Simple UNet based model that was aimed to perform semantic segmentation (per pixel classification)



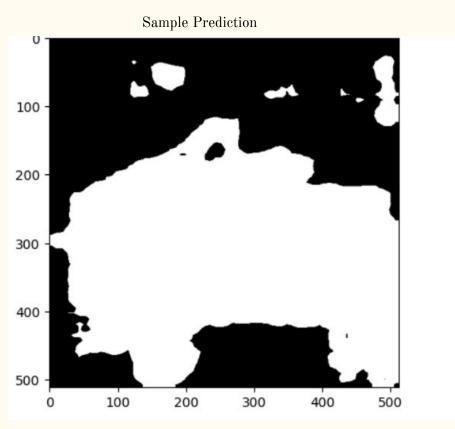


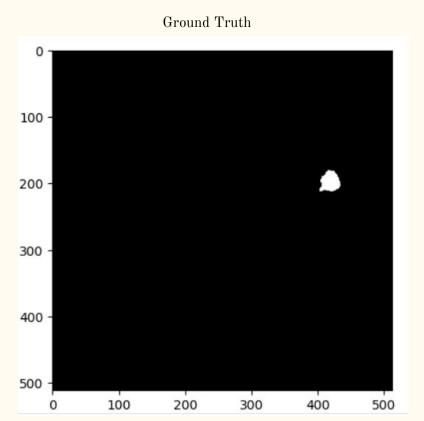




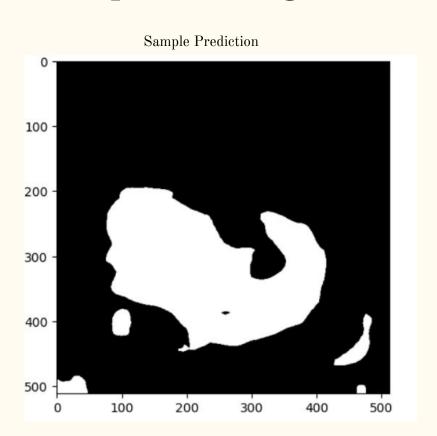


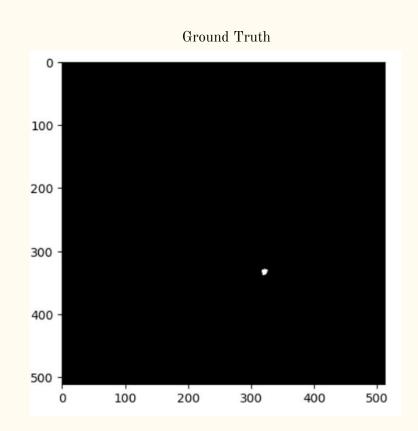
Sample Training Predictions



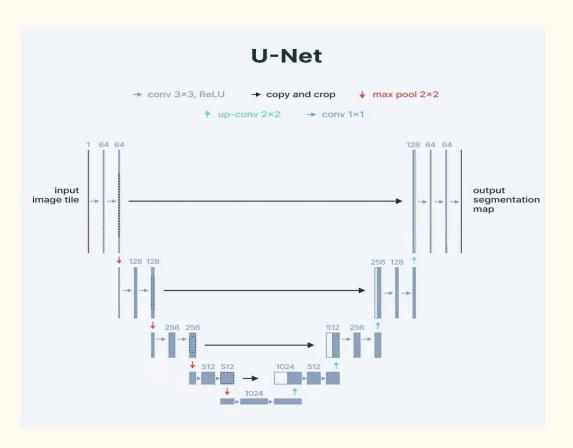


Sample Testing Predictions



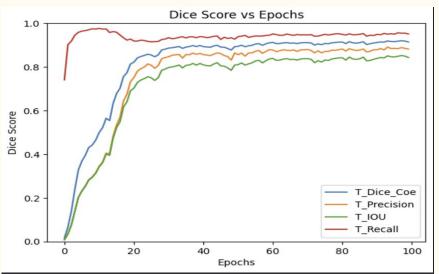


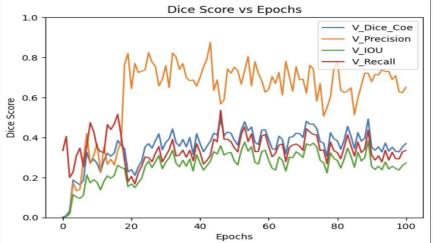
2D Segmentation with MobileNetV2



Model Training - 100 epochs

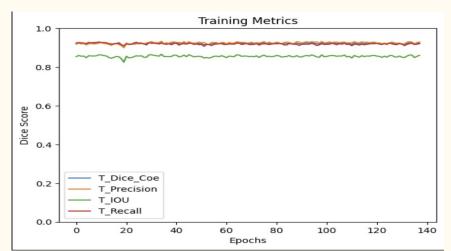
- Batch size: 16
- Input size: [16, 1, 256, 256]
- Output size: [16, 1, 256, 256]
- Learning rate: 1e-4
- BCE + Dice Loss function
- Weight factor for loss function: 100

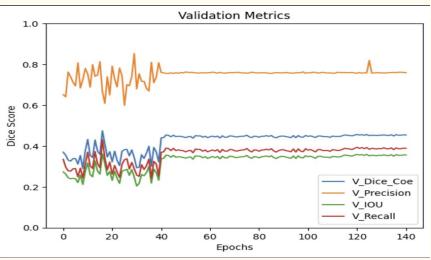




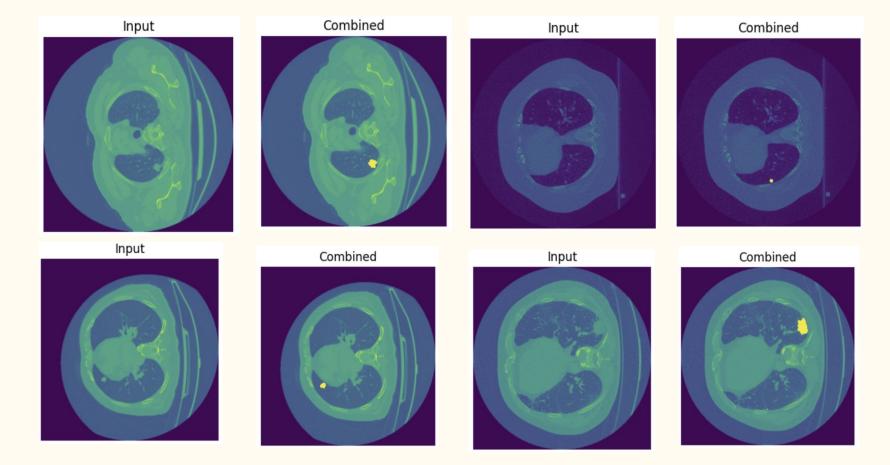
Model Training - 140 epochs

- Batch size: 16
- Input size: [16, 1, 256, 256]
- Output size: [16, 1, 256, 256]
- Learning rate: 1e-4
- BCE + Dice Loss function
- Weight factor for loss function: 1

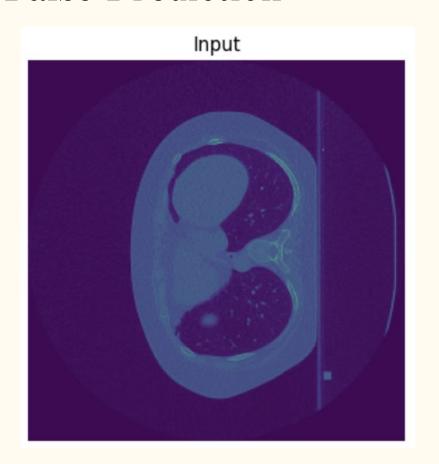


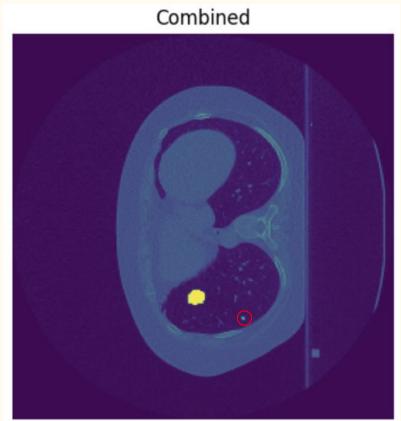


Correct Predictions

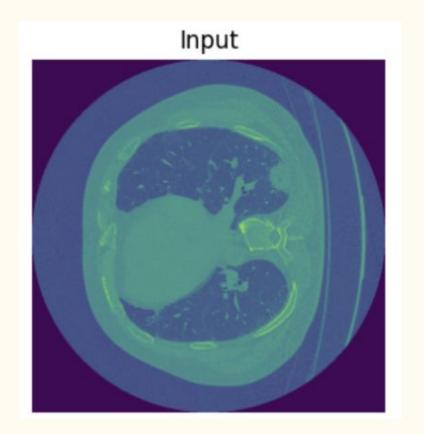


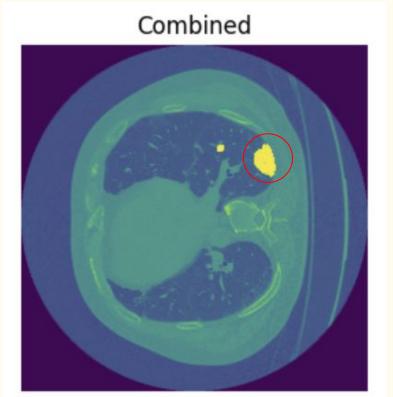
False Prediction





False Prediction





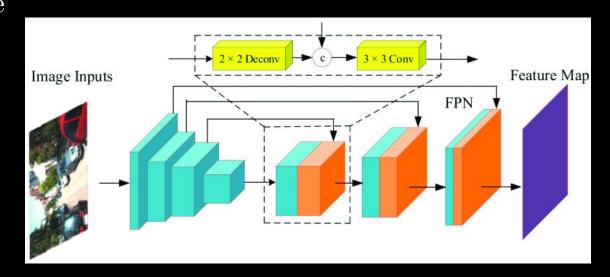
2D Segmentation with FPN & ResNet34

Batch size: 16

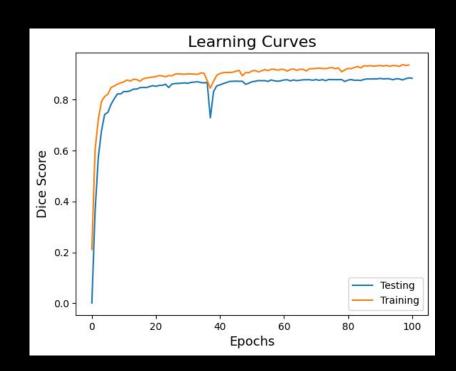
Learn rate: 0.0001

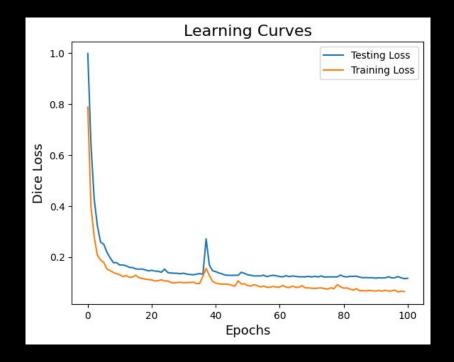
Epochs: 100

Loss: Dice

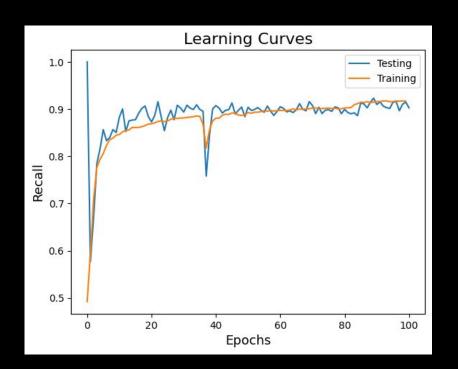


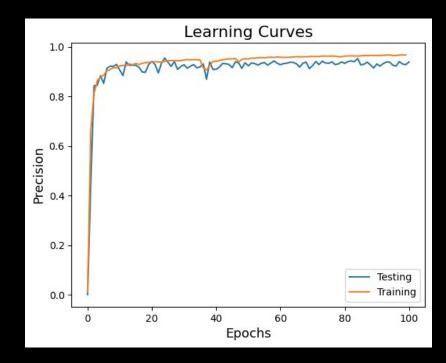
Performance: Dice Score & Loss



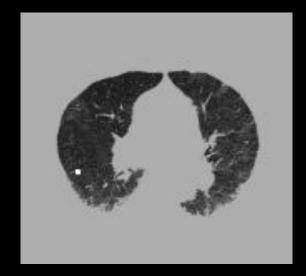


Performance: Recall & Precision

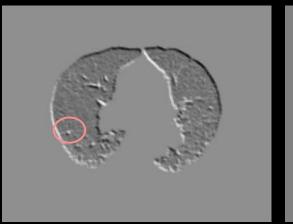




Conv Layer 1 Activations



Ground Truth

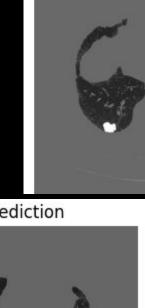




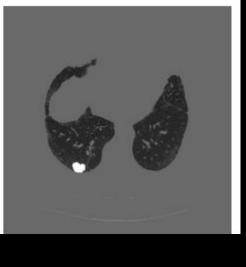




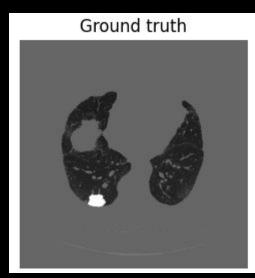
Predictions: Easy

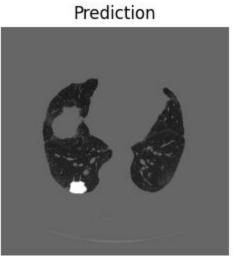


Ground truth

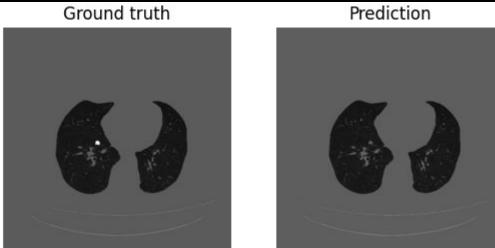


Prediction

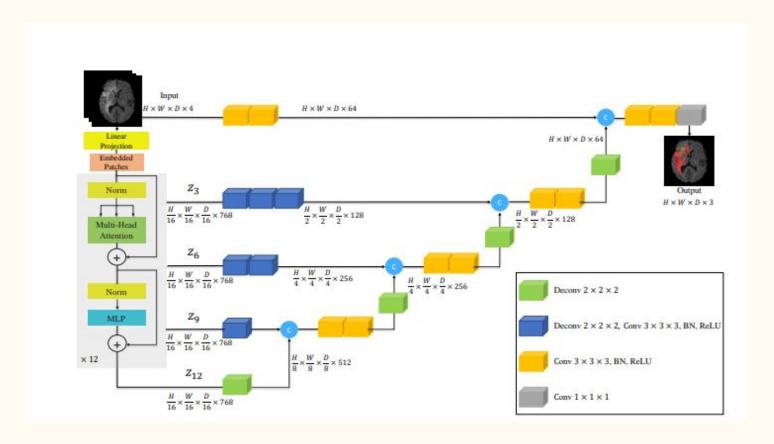




Ground truth Prediction Predictions: Hard



3-D Segmentation UNET-R

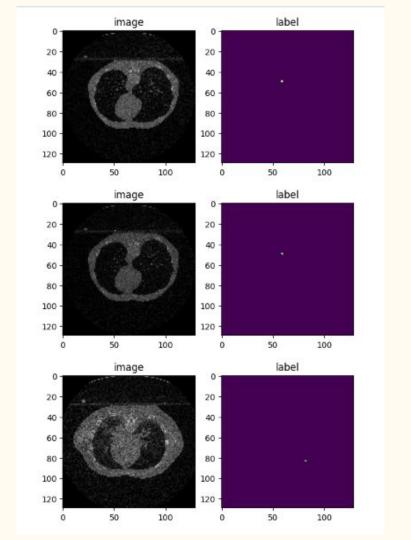


Dataset after Normalization and Transformation

Initial Dimensions 512x512

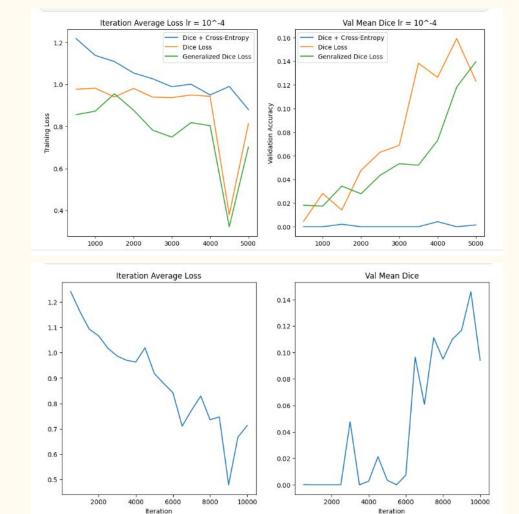
Current Dimensions: 128x128x128 (input as 16 patches of 64x64x64)

Image Values Normalized between [0,1]



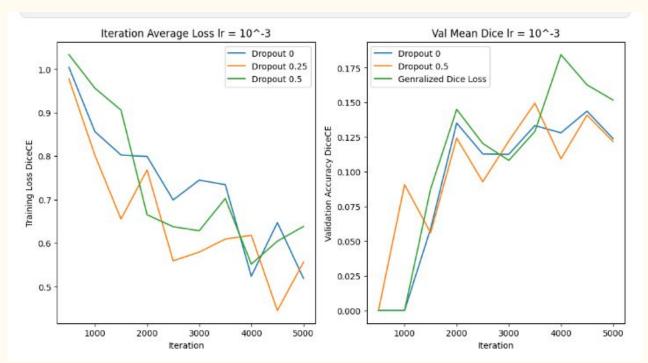
Loss Functions

- -5000 Epochs
- Batch Size 1 (18 3-D Images with randomized Rotations)
- -UNET-R (In: 16 (64x64x64) patches, Out: 1 channel)
- -DropOut
- -L2 Regularization weight decay = 10^{-4}
- -Learning rate = 10^-4
- -Choose Dice + CE since it had the highest score when ran for more epochs



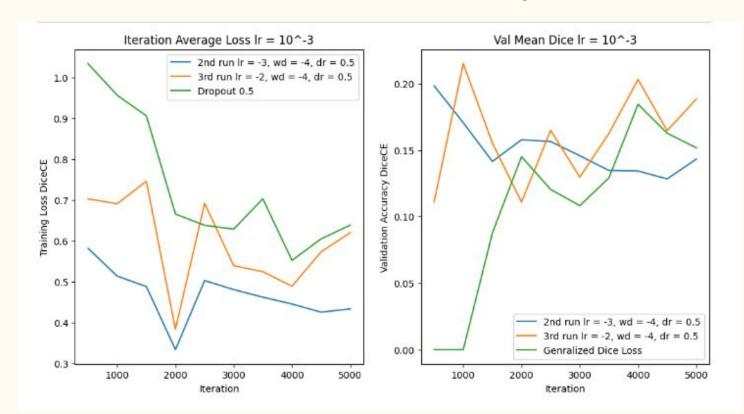
DropOuts

- -DropOut 0.0
- -L2 Regularization weight decay = 10^{-4}
- -Learning Rate = 10^-3



Learning Rates

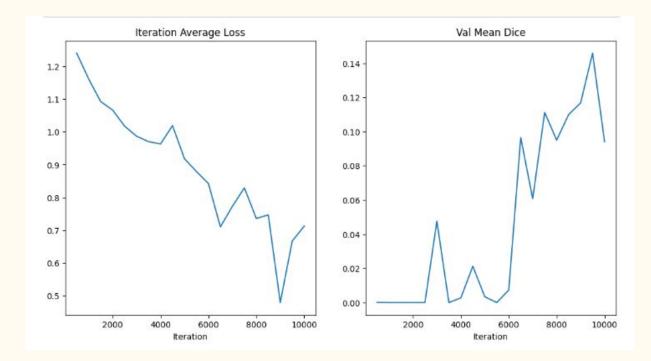
- -DropOut 0.5
- -L2 Regularization weight decay = 10^-4
- -Learning Rates = 10^-3 , 10^-4 , 10^-5



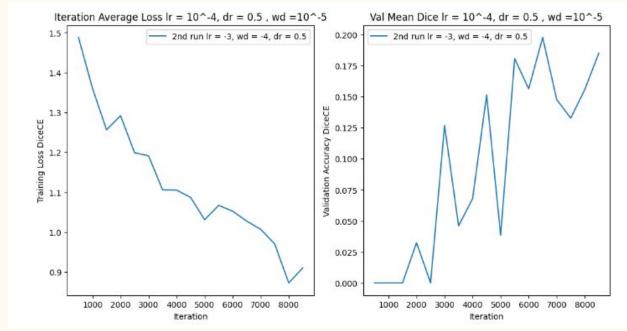
1-Channel Results



- Weight $Decay = 10^-5$
- DropOut = 0.5
- Weight tensor loss function ([100])
- 10,000 Epochs
- Outputs Discretized by 0.5 Threshold
- Highest Dice Mean Score around 0.15



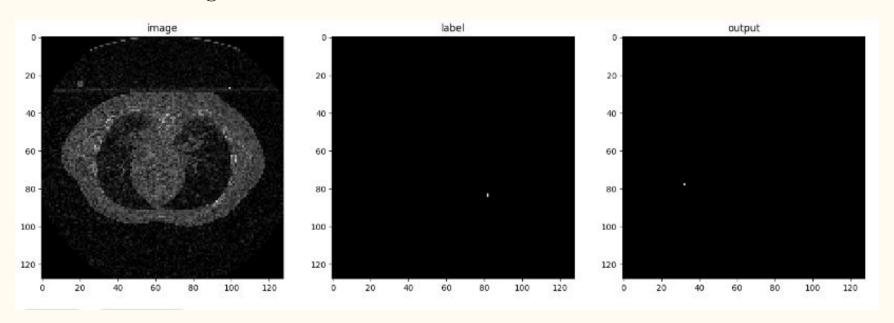
2-Channel + One_Hot_Encoding Approach



- Learning Rate = 10^-4
- Weight Decay = 10^-5
- DropOut = 0.5
- Weight tensor loss function ([0.1, 0.9])
- 10,000 Epochs
- Outputs Discretized using Argmax and One Hot Encoding
- Highest Mean Dice Score around 0.25

UNET-R Segmentation Results

Training 3-D Image was compared with Label. Black is background, White is Lung Tumor



Model Comparison

Model	Test Set Dice Score
Baseline Model	0.1
UNet/MobileNetV2	0.45
FPN/ResNet34	0.89
UNet-R	0.25

Github Repo

