Methods for Brain Tumor Segmentation and Survival Prediction



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Motivation

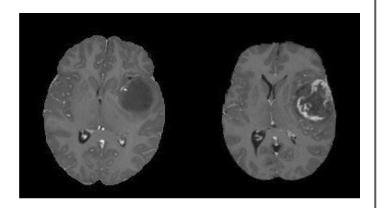


Context

Brain tumors are extremely life-threatening, survival rate of 33.4%

Glioblastoma is the most common form of brain cancer

Very people survive greater than 5 years (\sim 5%)



Motivation



Problem

Survival time prediction is vastly complex due to the amount of data required

Goal

Utilize Machine Learning methods to segment brain tumor images, extract features, and predict survival

Datasets



BraTS 2020 Challenge Dataset

Annually held competition

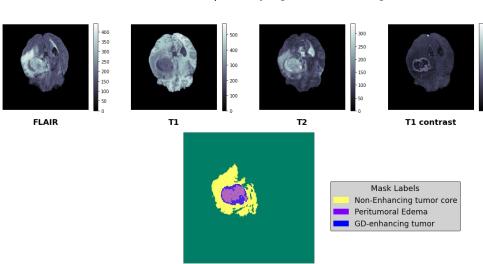
Multi-institutional data

Preoperative multimodal

MRI scans, particularly glioma



Multimodal Scans - Data | Manually-segmented mask - Target



Methods Overview



Segmentation
→ Autoencoder
→ Prediction

Assign each pixel a label (Tumor vs Background), isolating the tumor

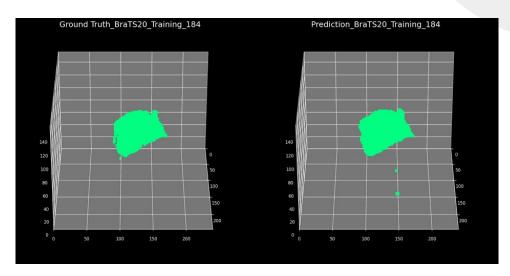
Encode high-dimensional info from segmentation into most prominent latent features

Predict patient survival days from the latent feature. Test performance against ground truth

Segmentation



- Objective: label brain tumor regions in 3D images
- Methodology: 3D-UNet architecture
 - Encoder
 - Bottleneck
 - Decoder for feature extraction.
- Good segmentation results comparing to ground truth



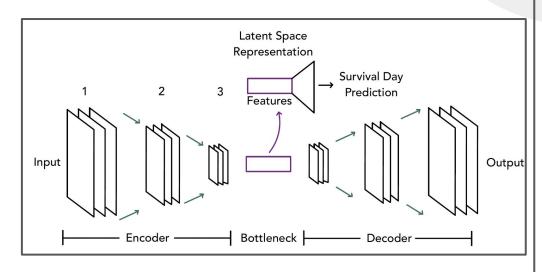
Ground truth

Segmentation

AutoEncoder



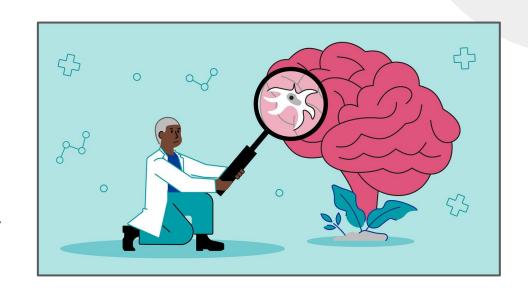
- Objective: Compress and reconstruct brain scan data.
- Structure: AutoEncoder considering 1) reconstruction loss and 2) survival prediction loss
 - Three convolution layers
 - Dropout
 - Skip layer



Prediction



- Objective: Predict survival days using latent features.
- **Methods**: Neural Network
 - PCA -> dimension reduction
 - Batch norm
 - Drop out
- Testing Metric:
 - Mean Square Error
 - SpearmanCorrelation



Results



Metric

$$ext{MSE} = rac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

+

Spearman Correlation

Strength of a monotonic relationship

Our Results

	MSE	Spearman
Survival Days	159197.84	0.4865
Patient Age	182.3997	0.5351

Literature Values

	MSE
Our Method	159197.84
Patel J. et al.	152467.00
Agravat R.R. et al.	116083.48
Soltaninejad M. et al.	109564.00

Discussion



Analysis

Skewed dataset leads to skewed predictions, majority of the survival times did not exceed 600 days → reflected in our results

Shortcomings

Lacked computational power, vast amounts of data needed to further improve the model

Future Steps

Refine our current model with extra time and resources, explore other prediction methods such as ensemble methods, hyperparameter tuning etc.

Citations



3D-unet medical image segmentation for tensorflow: Nvidia NGC. NVIDIA NGC Catalog. (n.d.). https://catalog.ngc.nvidia.com/orgs/nvidia/resources/unet3d_medical_for_tensorflow

Agravat, R. R., & Raval, M. S. (1970, January 1). 3D semantic segmentation of brain tumor for overall survival prediction. SpringerLink. https://link.springer.com/chapter/10.1007/978-3-030-72087-2_19

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Questions?

