MRI Glioma Tumor Segmentation with U-NET

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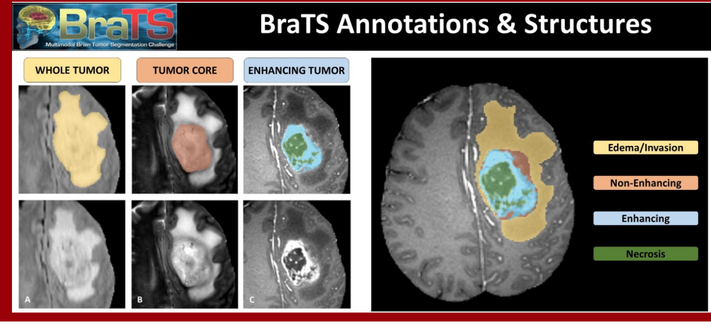


Abstract

Problem Statement

Brain Tumor Segmentation

- Classes: Non-tumor, edema, necrotic, core/non-enhancing, enhancing
- Current clinical mechanism - manual tumor segmentation from MRI images.
- Automation of this process is clinically relevant

Previous Work

- VGG16 + U-NET transfer learning + dropout
- SVMs and Fully Convolutional Neural Networks

Inputs

- Greyscale glioma MRI images, 4 per participant
  - Flair, t1, t1ce, and t2 scans

Outputs

- Predicted segmentation mask per class

Evaluation

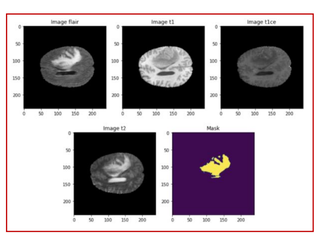
- Dice Coefficient, IoU score
- IoU score

$$Dice\ Coefficient = 2\frac{|P \cap T|}{|P| + |T|}$$

$$IoU\ Score = \frac{|P \cap T|}{|P \cup T|}$$

Dataset

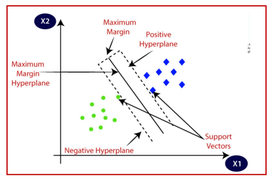
- BraTS 2020 Brain Tumor Segmentation
- 368 participants with glioma
- 368x4 = 1,472 MRI scans
- 4 classes
  - Non-tumor
  - Edema
  - Necrotic core/non-enhancing
  - Enhancing
- 70% training, 20% validation, 10% test
- Data normalization:

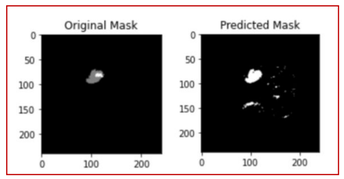


$$X = (X - X_{min})/(X_{max} - X_{min}).$$

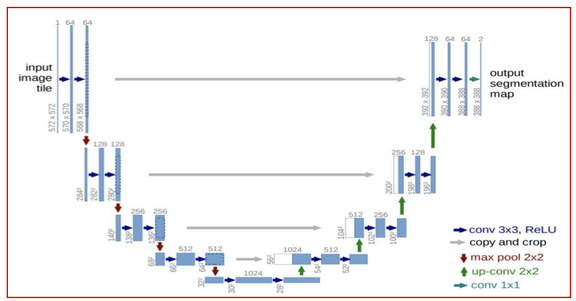
Methods

Support Vector Machine (SVM)

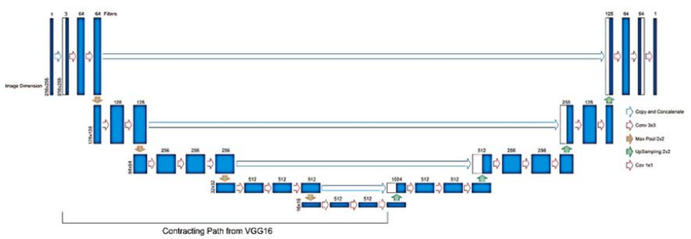




U-Net

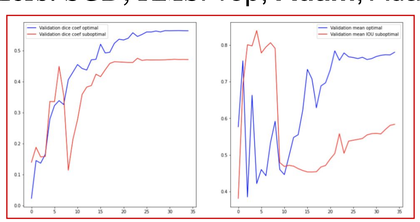


VGG16 U-Net / VGG19 U-Net

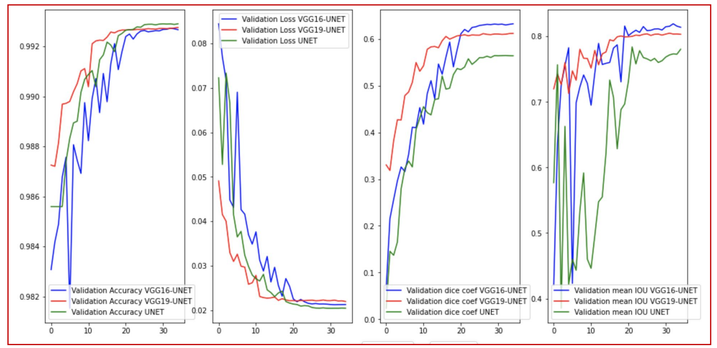


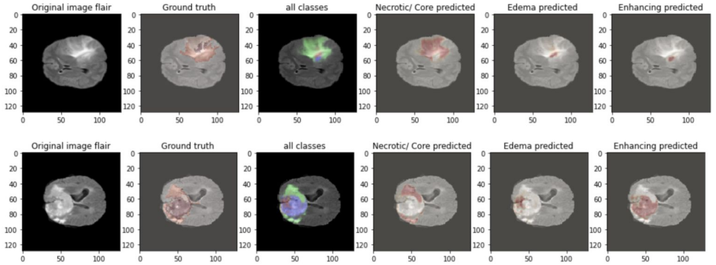
Hyperparameters

Learning rate: [0.0005, **0.0007**, 0.001, 0.005]
Dropout: [0.2, **0.5**, 0.7]
Data augmentation: [0.2, **0.3**, 0.5]
Optimizers: SGD, RMSProp, **Adam**, Adagrad



Results





Model	Dice Coefficient	Mean IoU
SVM	0.4367	0.6249
U-Net Suboptimal	0.4755	0.5835
U-Net Optimal	0.5648	0.7804
VGG-16 U-Net	0.6327	0.8191
VGG-19 U-Net	0.6121	0.8048

Conclusions and Future Steps

- Optimal Model: VGG16 - U-Net + 2D Spatial Dropout
  - Dice Score → Training: 0.6456: Validation: 0.6327, Test: 0.6501
  - Mean IoU → Training: 0.8136: Validation: 0.8192, Test: 0.8127
- Future Steps: spatially adapted normalization, elastic deformations, transfer learning