Brain Tumor Tissue Segmentation and Survivability Prediction

in BraTS 2020 MRI Scans

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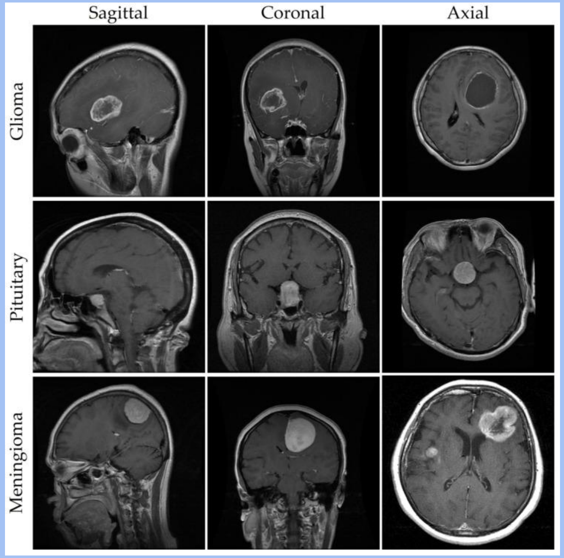
Brain Tumor Detection & Diagnosis

- **Brain Tumors**: Abnormal growth in the brain, can impair function if untreated.
- **MRI:** High-resolution, non-invasive brain imaging.
- **Challenges**:
  - Diagnosis depends on variable MRI image quality and expert interpretation.
  - Invasive biopsies accurate, but painful and prone to errors.
- **Solution**:
  - Computer Vision: Improves tumor detection, segmentation, and classification.
  - Enables faster, accurate, and consistent diagnosis.



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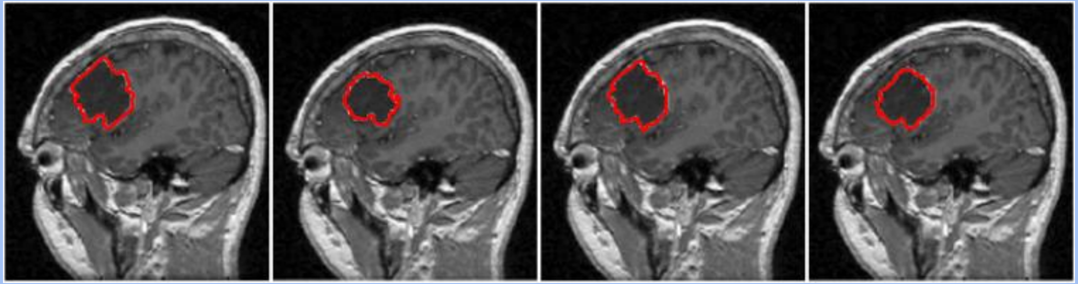
Prognosis & Survivability of Brain Tumors

Predicting survivability directly from MRI scans can be very useful.

Challenges: Manual segmentation/annotation and prognosis prediction of MRIs is inconsistent and subjective.

Solution: DL-based segmentation of MRI Images → + Age, prediction of Survival with two separate models

Benefits: Consistency, can offer insight into correlation between tissue type and prognosis



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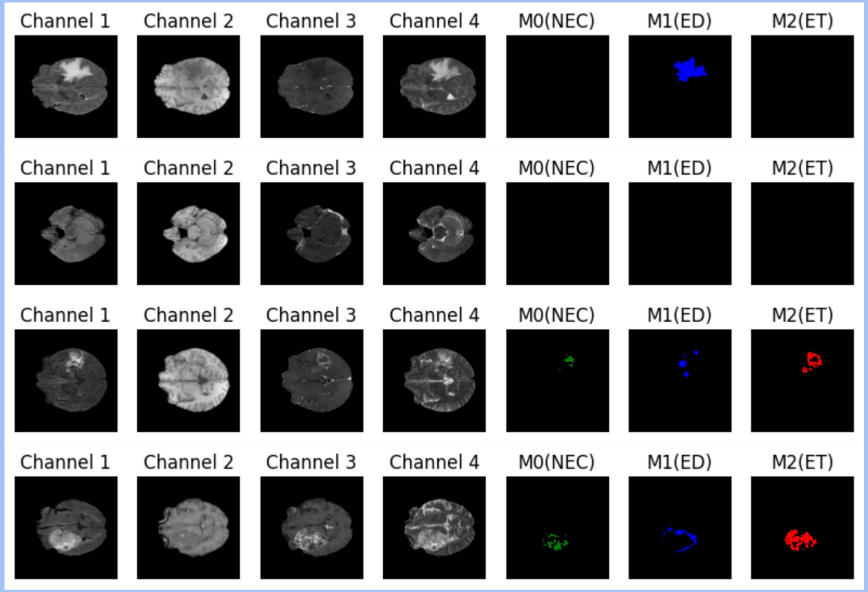
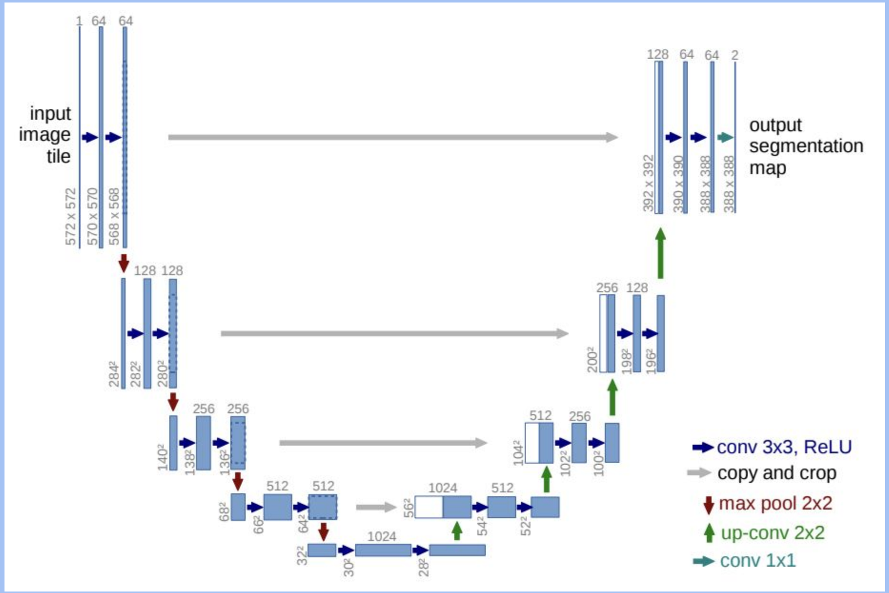
The Dataset (BraTS 2020)

- **Images**: Multimodal MRI scans: T1, T1Gd, T2, T2-FLAIR
  - Pre-processed: co-registered, 1 mm^3 resolution, skull-stripped
- **Masks**: 3 Channels - Necrotic/non-enhancing tumor core (NEC), Peritumoral edema (ED), Enhancing tumor core (ET)
- **Survival Data:** age, #days, extent of resection (EOR)



Segmentation (UNet-based)

- **Data Preprocessing** - Images/masks resized to 256 × 256, split 80-10-10 (train/val/test).
- **UNet** - Biomedical Image Segmentation Model, ResNet-18 encoder with ImageNet weights, customized segmentation head
- **Dice Loss** - weighted to address class imbalance, measures pixel overlap
- Trained with full original model, then fine-tuned with everything frozen except custom segmentation head.



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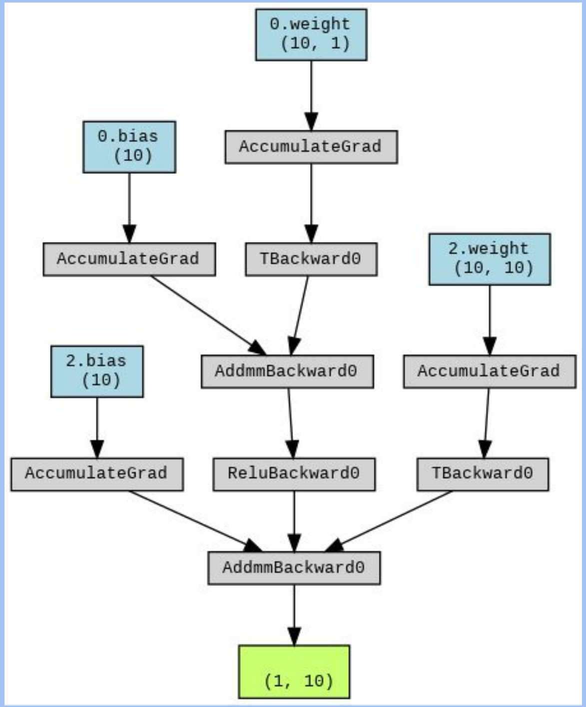
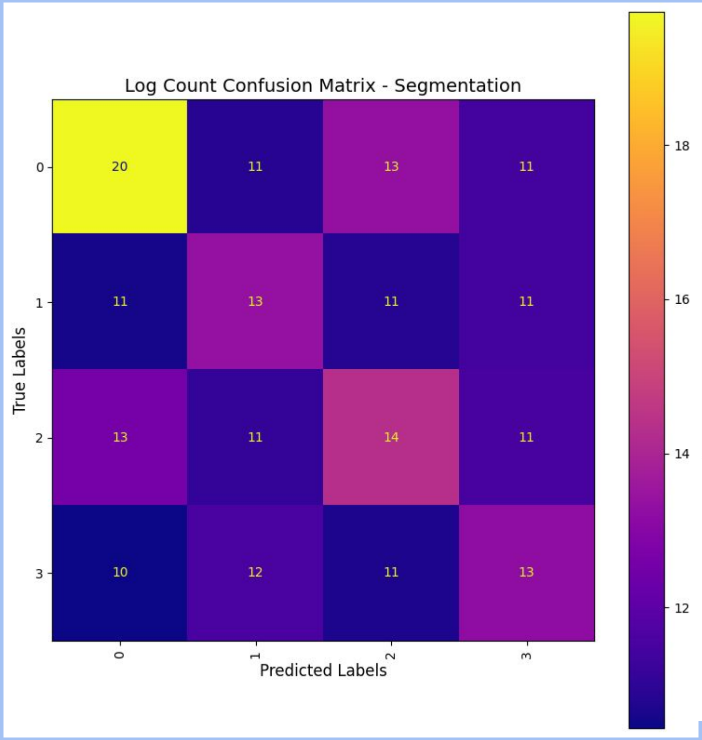
Classification (ResNet50-based)

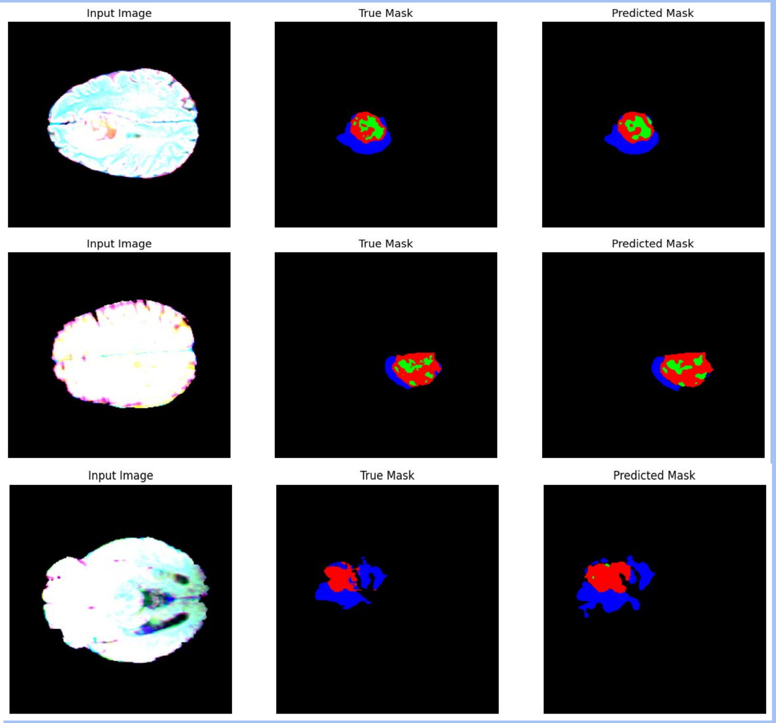
- **Survival Data Preprocessing:** Categorized into three quantile-based bins:
  - **Short:** 5–265 days
  - **Medium:** 268–476 days
  - **Long:** 486–1767 days
- **Mask Preprocessing:** Masks resized to 224 × 224, stratified split 80-10-10 (train/val/test).
- **Resnet50:** Pre-trained on ImageNet with custom output layers and an age processing layer for combined mask and age feature classification.
- Trained the full original model with early stopping. Evaluated using cross-entropy loss



Custom age processing layer

Results - UNet

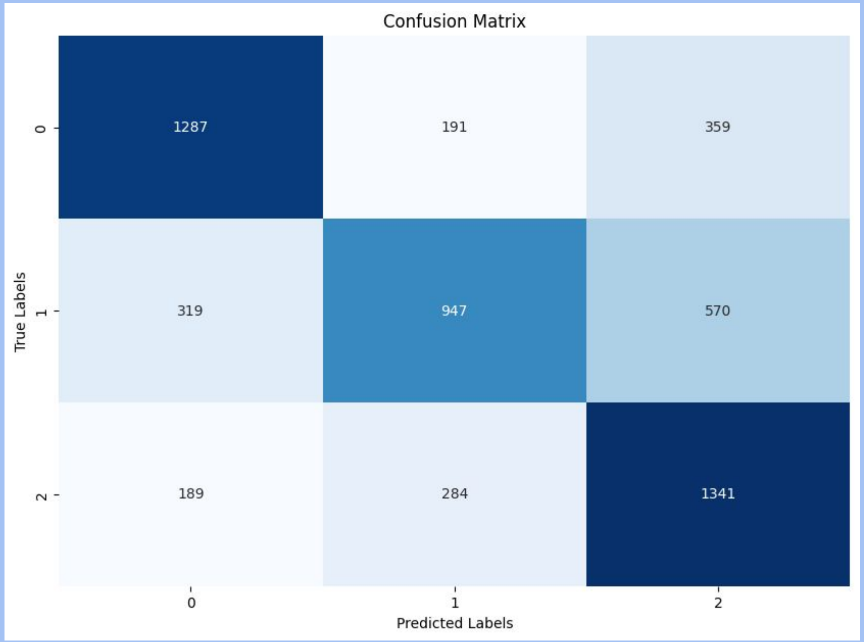




Overall Testing Accuracy: **0.8986**

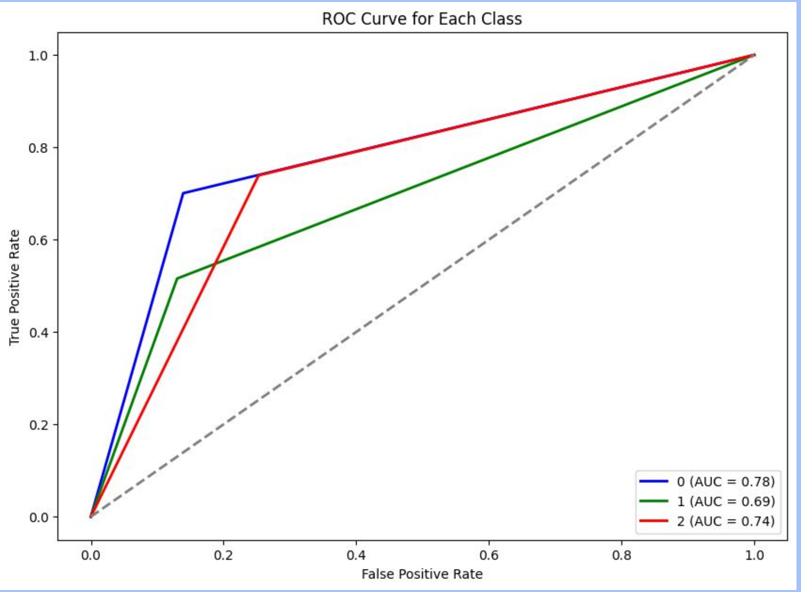
By Channels:
NEC = **0.8728**,
ED = **0.8275**,
ET = **0.8942**.

Results - ResNet50

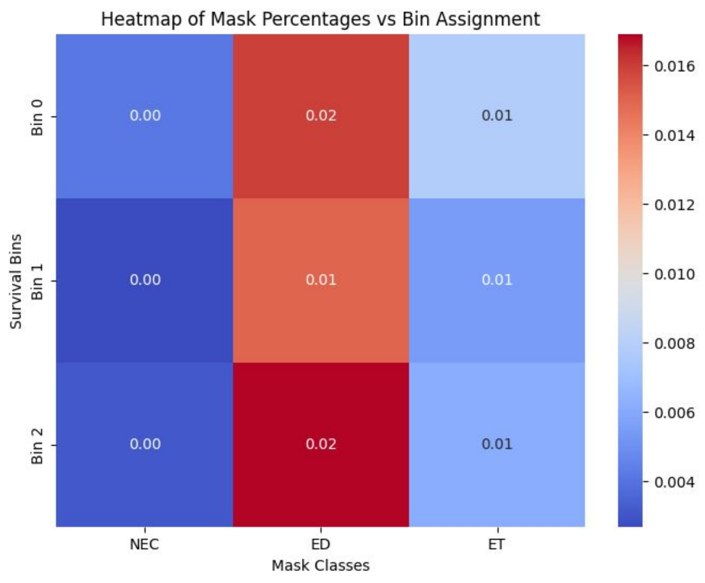


Test Loss: 0.6613
Test Accuracy: 0.6515

Bin	Accuracy
0	0.7006
1	0.5158
2	0.7393



Results - UNet + ResNet50



Before removing all black masks (Overall: 0.6014)

True Bin	Image Wise Acc(%)
0.0	0.6473
1.0	0.4586
2.0	0.6996

After removing all black masks (Overall: 0.8692)

After removing all black masks + majority vote across volume (Overall: 0.9831)

True Bin	Image Wise Acc(%)	Maj Vote Acc(%)
0.0	85.488127	97.625330
1.0	87.688098	99.316005
2.0	87.755102	97.959184

Future Directions

- **Input Data Expansion:** Incorporate axial, sagittal, and coronal images as input channels for segmentation and classification model
- **Data Augmentation:** Implement data augmentation techniques (e.g., rotation, flipping, brightness adjustments)
- **Volume-Based Processing:** Modify the ResNet50 model to take in all slices of a given volume as input channels instead of individual masks
- **ResNet Variants**: Evaluate the performance of other ResNet variants (e.g., ResNet34, ResNet101) for both segmentation Encoder and the Survival Classification Model

References

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Thank You