Ablate the number of necessary MRI sequences for glioma classification using 3D-ResNet

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Motivation

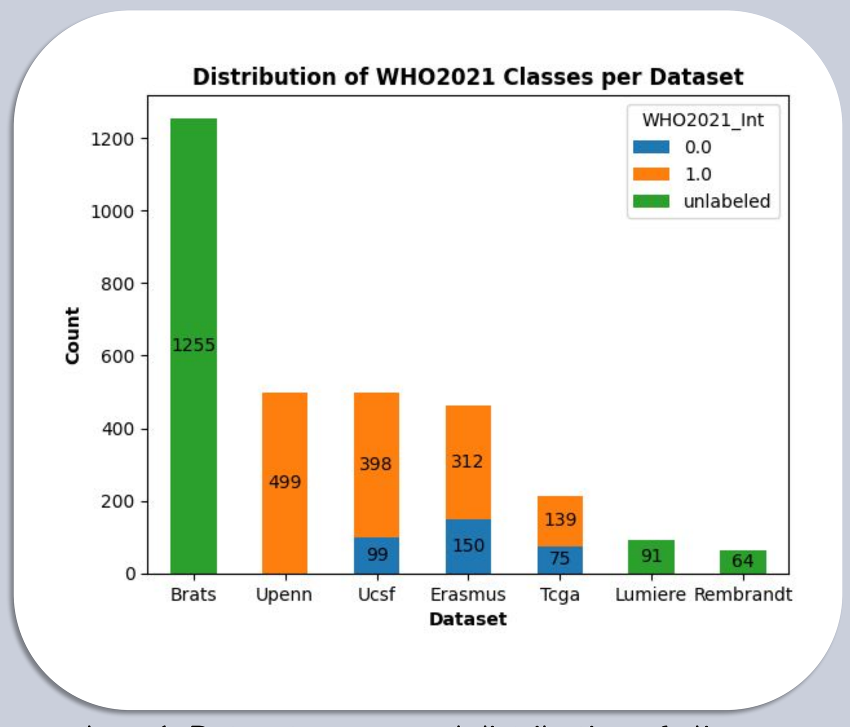
Glioma is a challenging type of brain tumor, that presents diagnostic complexities. Deep learning has emerged as a promising non-invasive method for glioma classification. **However, acquiring multiple brain MRI modalities (T1, T1C, T2, FLAIR) can be tedious.** This project aims to answer the following research question:

Which is the optimal sequence of brain MRI modalities that yields the highest performance in glioma classification?

Dataset

Our final dataset consists of 7 publicly available datasets containing brain MRI scans:

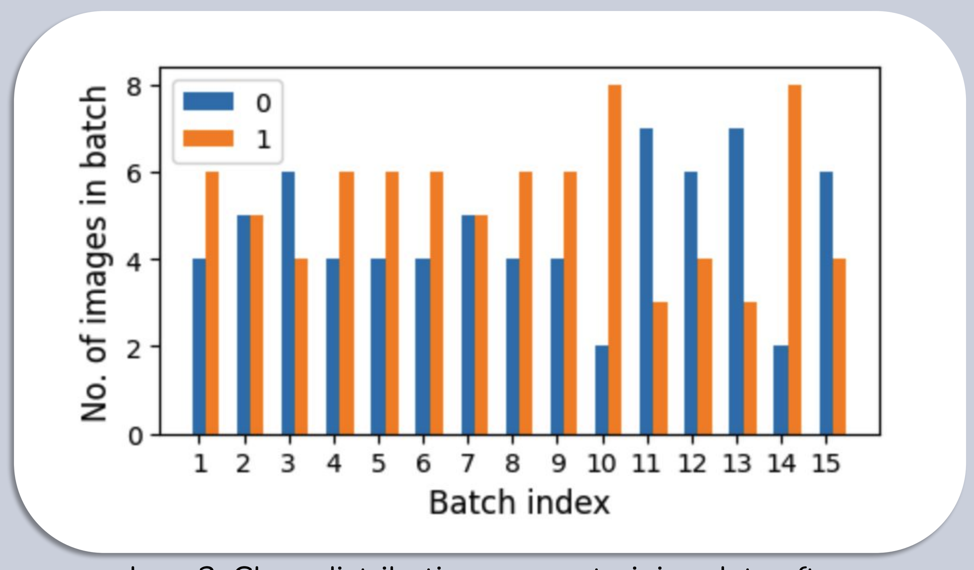
- Each scan consists of 4 modalities: **T1, T1C, FLAIR, T2,** and a tumor **segmentation mask**
- **Unlabeled datasets were dropped** in the preprocessing step
- **TCGA** dataset was kept out for **testing**, **the rest** of the datasets were used for **training/validation**
- **Astrocytoma** and **oligodendroglioma** were combined under **Class 0**
- **Glioblastoma** represents **Class 1**



Img. 1: Dataset names and distribution of glioma classes among them.

Challenges

1. **Class imbalance**

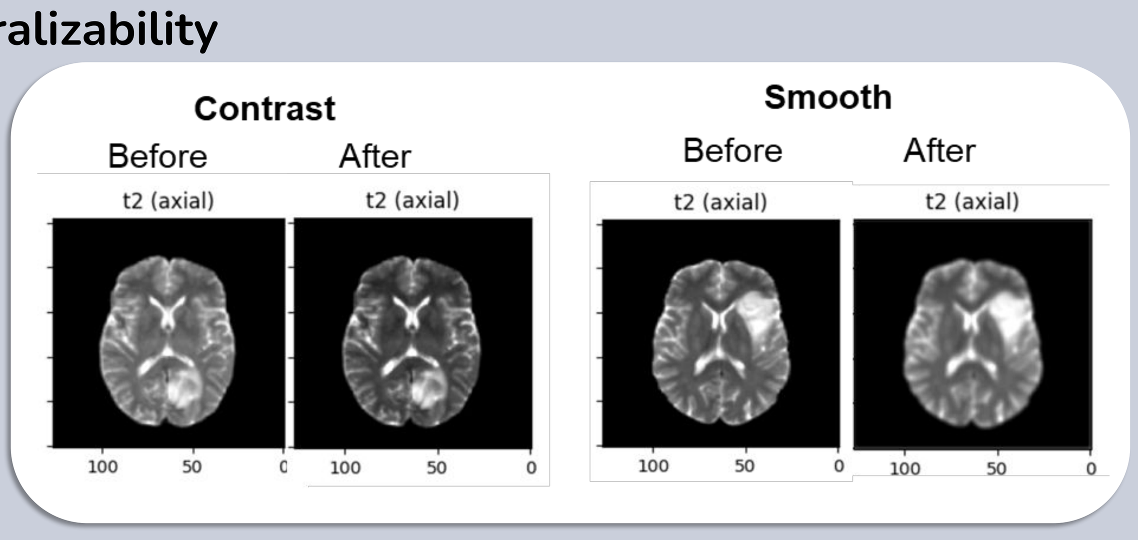


Img. 2: Class distribution among training data after

Solution:
Applying weighted sampler to the training data

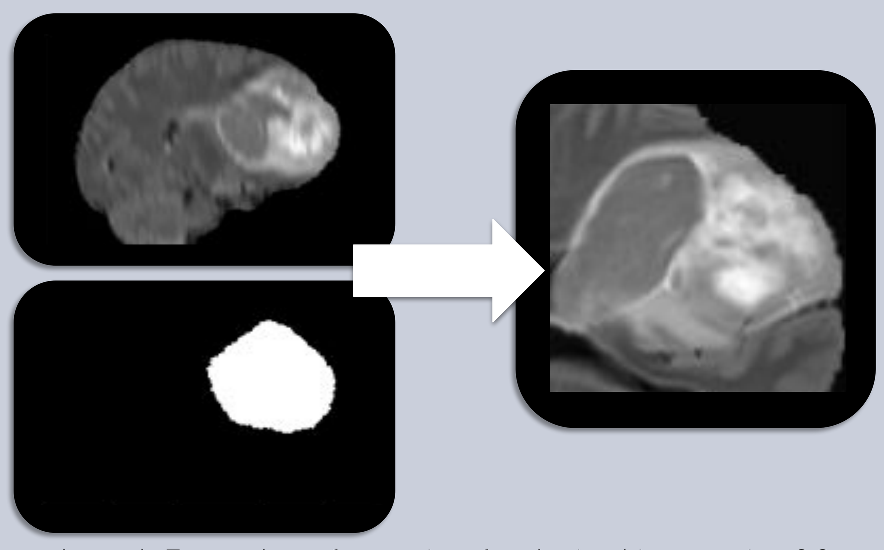
2. **Bad model generalizability**

Solution:
Applying **data augmentation** transformations from MONAI [2] to the training data



Img. 3: Examples of applied transformations: **Contrast and Smooth**

3. **Modalities have different resolutions**



Solution:
Crop images around tumor regions based on given segmentations instead of resizing them

Img. 4: Examples of cropping for desired image size 96

Results

We conducted **4 stages** of experiments*:

1. To identify the **best training set-up** for ResNet34 for combination of all modalities:

Mode	Cropped	ACC	F1	MCC	AUROC
Training from scratch	True	0.78	0.85	**0.50**	0.86
Training from scratch	False	0.71	0.78	0.36	0.74
Fine-tune all weights**	True	0.75	0.82	0.44	0.80
Fine-tune only last Residual block**	True	0.57	0.69	0.00	0.49

** MedicalNet: 3D-ResNet pre-trained on medical data[1]

2. To identify the **best combination of modalities** with the best set-up from *step 1*:

Model Nr.	Modalities	ACC	F1	MCC	AUROC
M1	flair, t1c, t2	0.84	0.88	**0.64**	0.88
M2	t1c	0.82	0.87	0.60	0.87
M3	t1c, t2	0.81	0.86	0.57	0.85
...					
M14	flair, t1	0.66	0.76	0.23	0.67
M15	t1	0.59	0.73	0.00	0.56

3. To compare if deeper network (i.e., ResNet50) produces better results on top 3 combinations from *step 2*:

Modalities	ACC	F1	MCC	AUROC
flair, t1c, t2	0.80	0.85	0.57	0.86
t1c, t2	0.78	0.82	0.54	0.88
t1c	0.70	0.78	0.32	0.77

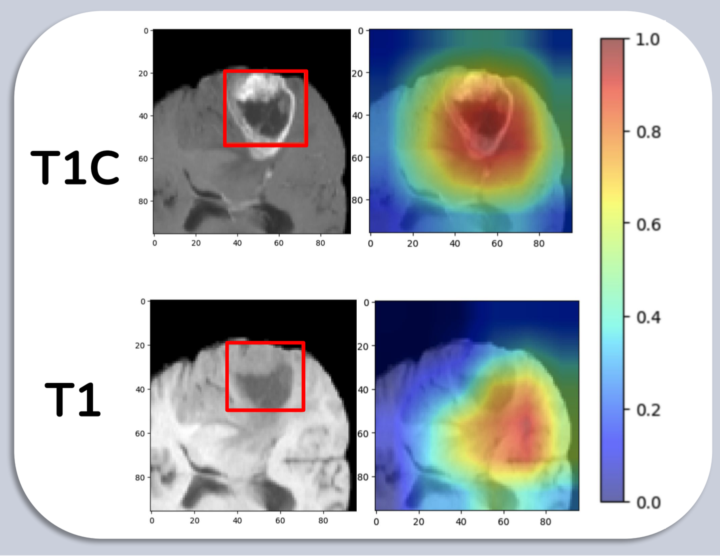
4. In the final step we **extended our method to semi-supervised** by labelling unlabeled images using ***Model M1***, thus, enhancing our training dataset. We then trained ResNet34 on best combination from *step 2* using enhanced dataset:

Modalities	ACC	F1	MCC	AUROC
flair, t1c, t2	0.83	0.88	0.62	0.86

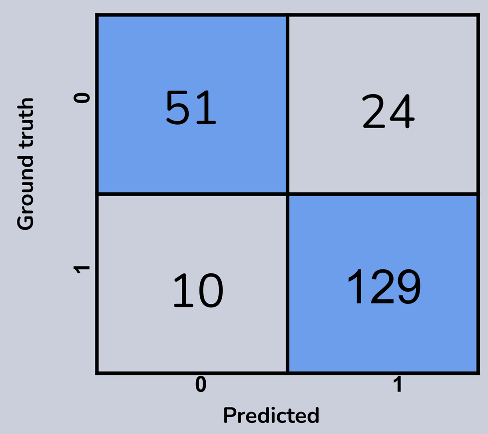
**in the experiments with >1 modality, the modalities were stacked and each modality was treated as a separate input chanel*

Discussion

- **T1C**, being a contrast-enhanced modality, **has the greatest impact** on the model's performance, as anticipated when examining blood-brain barrier breakdown, such as tumors (Img. 5)
- **The utilization of all modalities** or **complex architectures like ResNet50** introduces increased model complexity, resulting in suboptimal performance compared to simpler models
- **Cropping images around the tumor** leads to substantial performance improvement by directing the model's attention to the tumor area



Img. 5: GradCAM heat map: T1 vs T1C.



Img. 6: Confusion matrix of Model M1.

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References

[1] https://huggingface.co/TencentMedicalNet/MedicalNet-Resnet34
[2] MONAI: An open-source framework for deep learning in healthcare