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FEDERAL NEUROSURGICAL CENTER NOVOSIBIRSK

The Siberian Multimodal Brain Tumor Image Segmentation dataset

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Background

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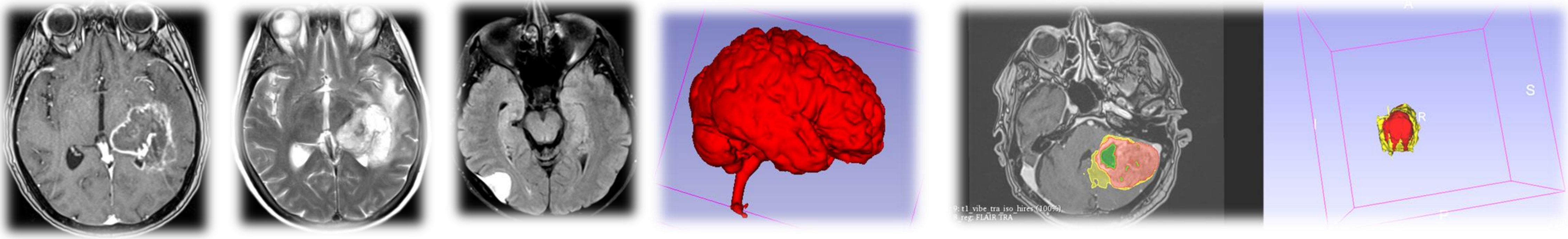
- Increase in the number of neuro-oncological patients (Novosibirsk region ~ 600 patients per year, and up to ~ 2000-3000 patients with brain metastases)
- MRI - the "gold standard" for detecting brain tumors, marking the surgical field and postoperative monitoring in neurooncology
- Increasing the work stress for doctors (radiologists, neurologists, neuro-oncologists)
- Increasing risk of «human error» and «medical error»
- A large amount of visual diagnostic material and new MRI technologies
- New requirements for the quality of medical care

RFBR research project 19-29-01103. Goals

- To create a dataset, which includes a complete clinical diagnosis, a detailed description of pathological manifestations, protocols of operations, data on the postoperative course with histology and immunohistochemical examination.
- To develop protocols for manual and automatic segmentation of MRI images in the DICOM format .
- To develop methods of segmentation, detection and classification brain tumors on the base of artificial intelligence (convolutional neural networks).



Clinical base - FSBI «Federal Neurosurgical Center», Novosibirsk

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The main activity of the Center is to provide medical hi-technological neurosurgical care.

Neurooncology (≈ 600 brain surgeries per year)

- High operation precision is based on the microanatomy and neurophysiology, application of neuronavigation before and during the surgical procedure.
- Pre-op examination including MRI or multi-level spiral CT with contrast, tractography, non-invasive variants of angiography, allows planning operation process in detail, avoiding affection of functional cerebral cortex zones and also vascular structures.
- Facilities of OR and experience obtained during different foreign educational courses and training, allow performing either all types of minimally invasive or any types of approaches to the skull base necessary for removal of complex basal tumors with minimal affection to the brain.

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Radiodiagnosis (≈ 5000 screenings per year, including ≈ 1000 brain screenings)

- The equipment of the Department allows performing maximally executive check-up of a patient using the whole range of diagnostics capabilities (ultrasound investigation, CT, MRI, digital X-ray scanning).
- Specialists study new methods, and diagnostic directions, striving at their implementation in our center.
- They actively participate in the researches connected with the neurovisualization.

Visualization of brain structures on a 1.5 T magnetic resonance imager (Siemens Magnetom Avanto)

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Pulse sequences	Scan Parameters					
	TR (ms)	TE (ms)	Cut thickness (mm)	FOV (mm)	Voxel (mm)	Scan time min: sec
Localazer						
1. t2_tse_tra (T2-WI)	5000	91	5.0	230	0.8x0.6x5.0	1:32
2. diffusion (DWI)	3400	102	5.0	230	1.2x1.2x5.0	0:53
3. t2_tse_SAG (T2-WI)	5000	91	5.0	230	0.8x0.6x5.0	1:32
4. t2_swi3d_tra_p2_fast (T2-SWI)	49	40.0	2.0	230	1.1x0.9x2.0	3:29
5. t1_vibe_tra_iso_hires (T1-WI)	6.16	2.39	1.0	256	1.0x1.0x1.0	3:06
CONTRAST (Gadodiamide - 0.1 mmol / kg body weight - volume from 10 to 20 ml)						
6. t2_tirm_tra_dark-fluid (T2-FLAIR)	7500	92	5.0	230	0.9x0.9x5.0	3:47
7. t1_vibe_tra_iso_hires (T1-WI)	6.16	2.39	1.0	256	1.0x1.0x1.0	3:06

Dataset – data processing

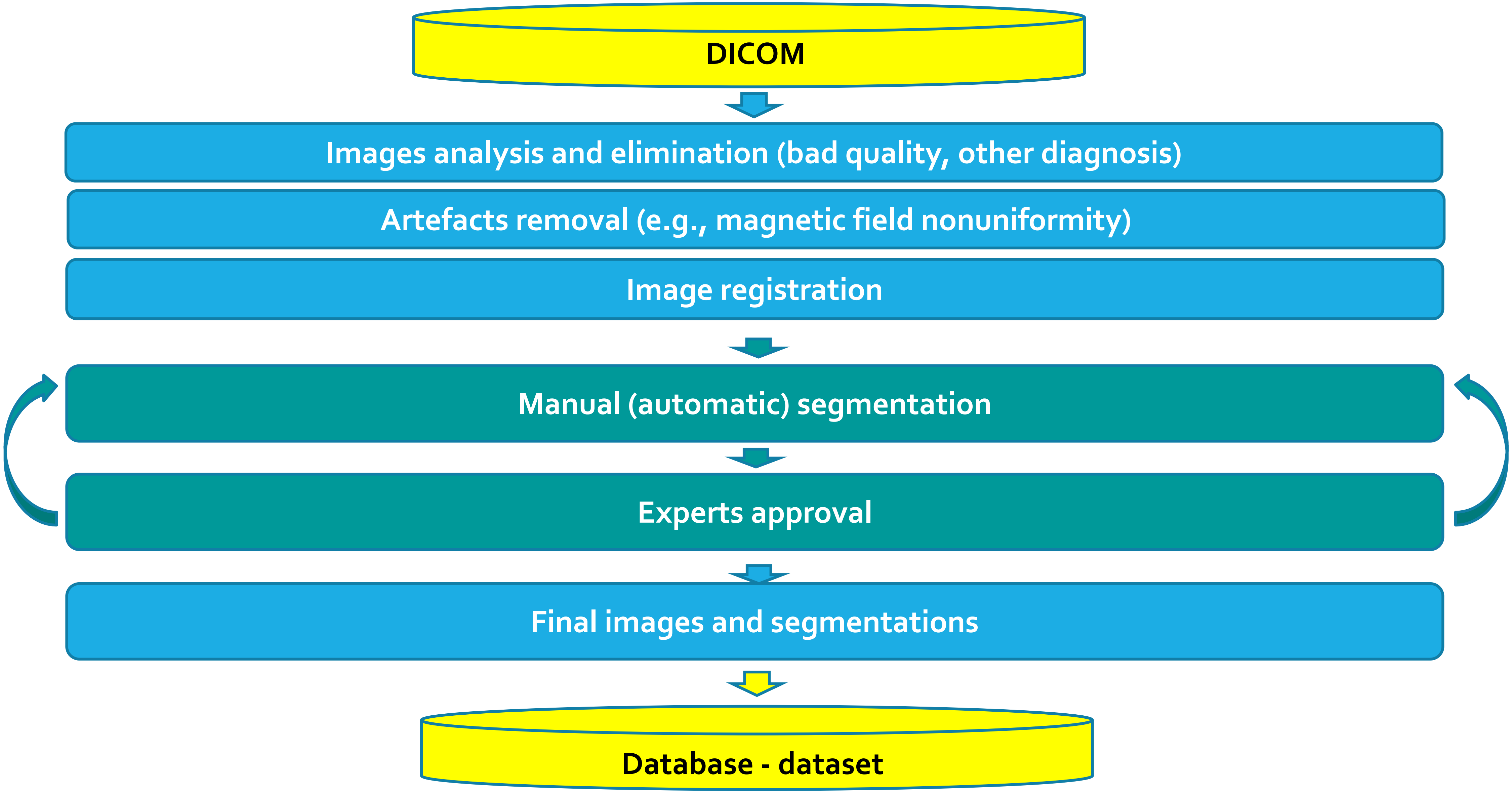
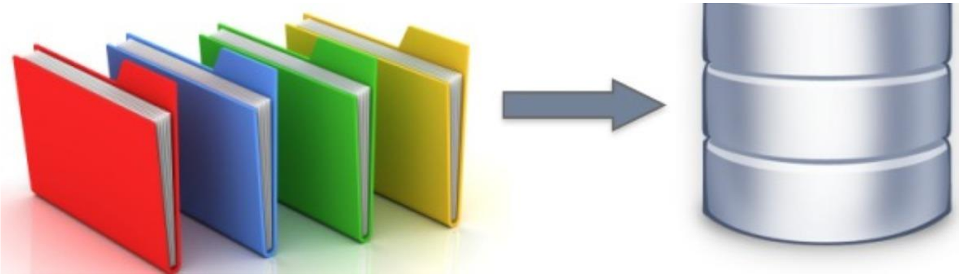


Image registration

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. Image registration geometrically aligns two images—fixed and moving images.

The fixed image		The moving image
Base patient (T1-CE)	←	Current patient (T1-CE)
Current patient (T1-CE registered)	←	Current patient (T1, T2, FLAIR)

Dataset



	received & anonymized*	registered	automatic segmentation	manual segmentation	plans
astrocytoma		70	60	10	30
glioblastoma		140	110	30+5	50
meningioma		160	130	30+5	50
neurinoma		130	100	30+5	100
TOTAL	**761***	**500**	**385+15**	**100+15**	**230**

*Including interesting clinical cases: pseudotumors, another tumor types, images after surgery AND bad quality images.

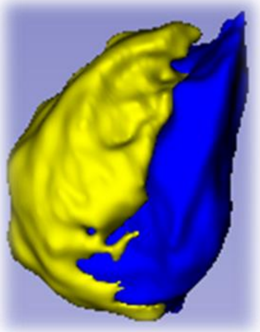
3D Slicer - the free cross-platform open-source medical image processing and visualization system

- Image registration
- Manual segmentation
- Approving & correction segmentation by experts

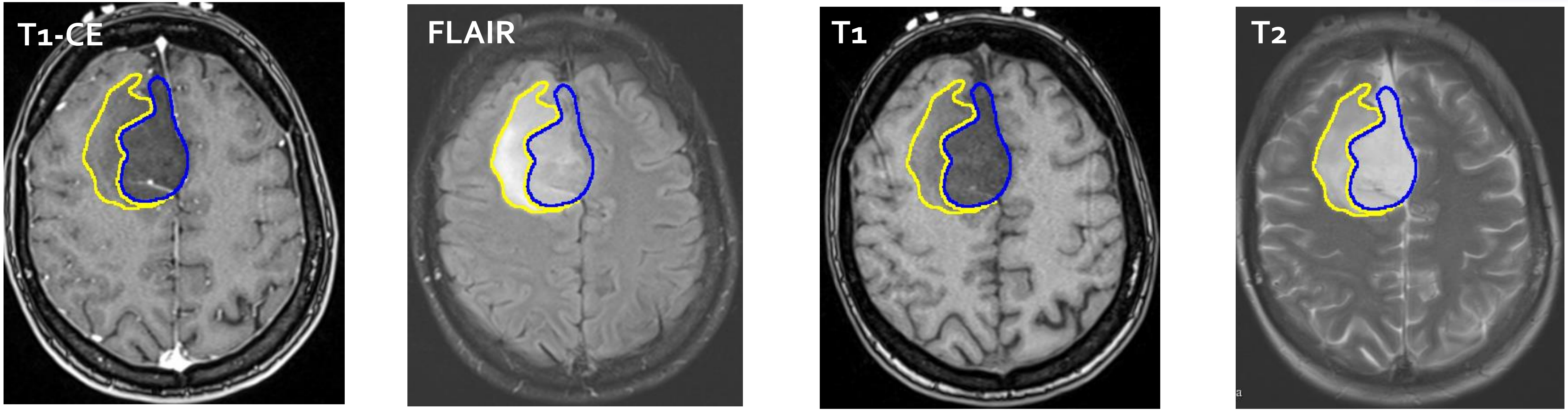
3DSlicer

Our plans: to develop a 3D Slicer module for automatic segmentation

www.slicer.org



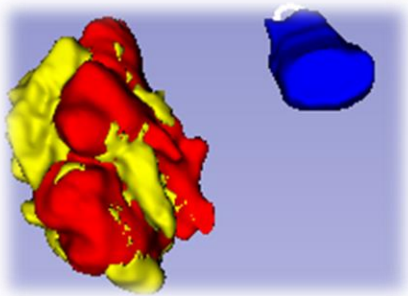
Astrocytomas (70)

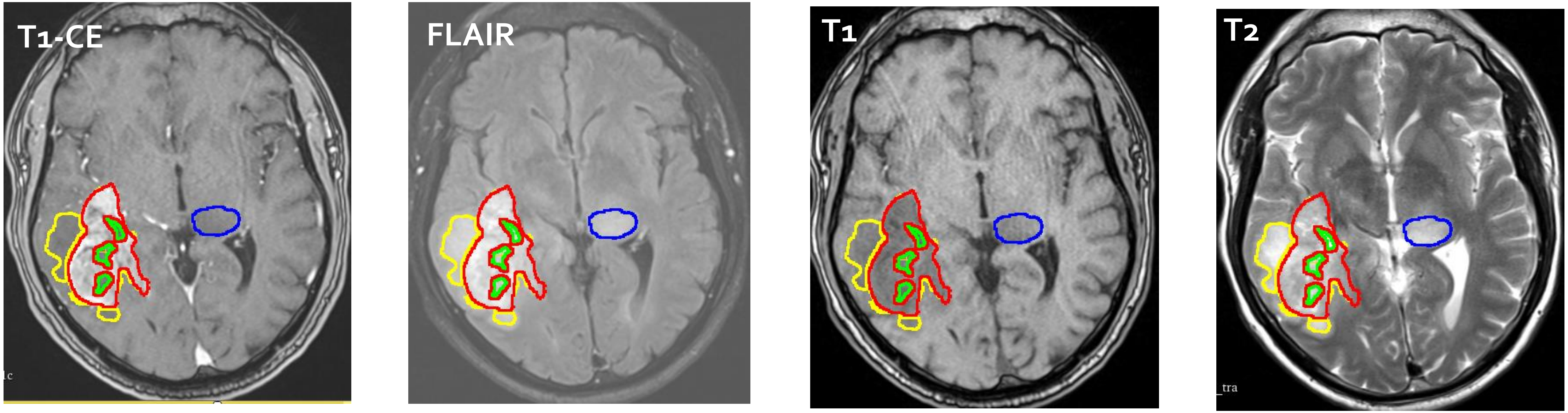


39% male. Median age – 37, IQR – [31; 56] years.

The annotations comprise the labels of the peritumoral edema (yellow), the non-enhancing tumor (blue), GD-enhancing tumor (red), and the necrotic tumor core (green).

Glioblastomas (140)

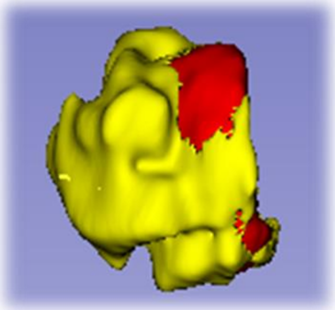


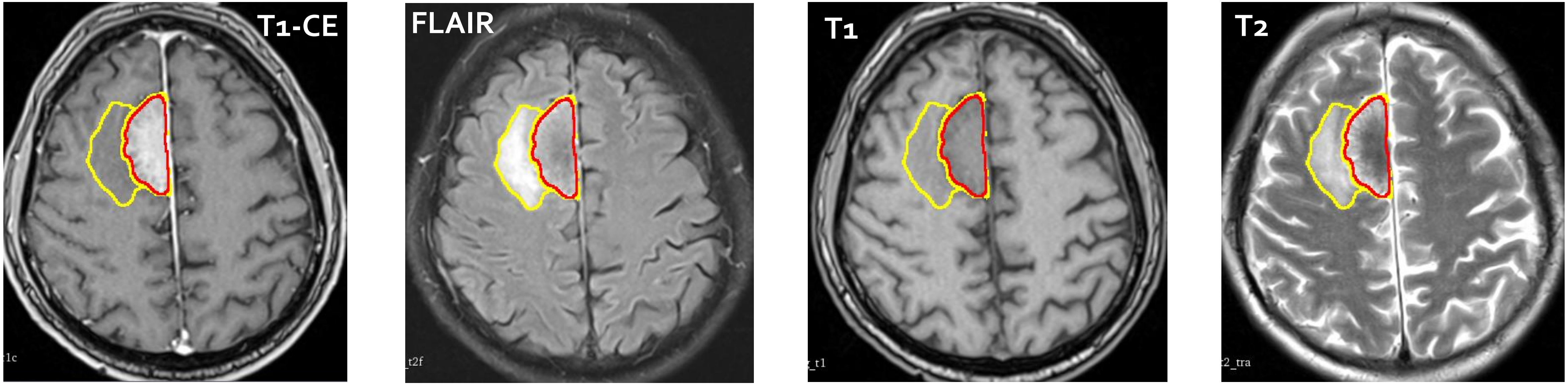


53% male. Median age – 57, IQR – [48; 63] years.

The annotations comprise the labels of the peritumoral edema (yellow), the non-enhancing tumor (blue), GD-enhancing tumor (red), and the necrotic tumor core (green).

Meningiomas (160)

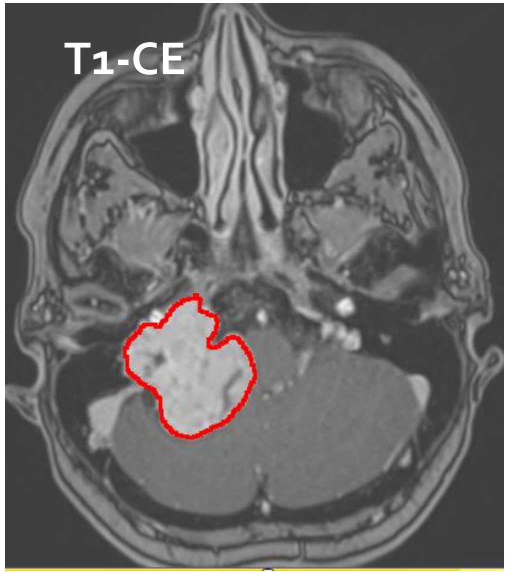


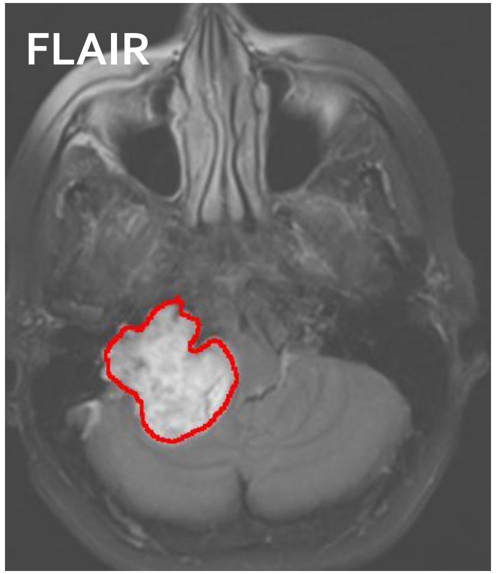


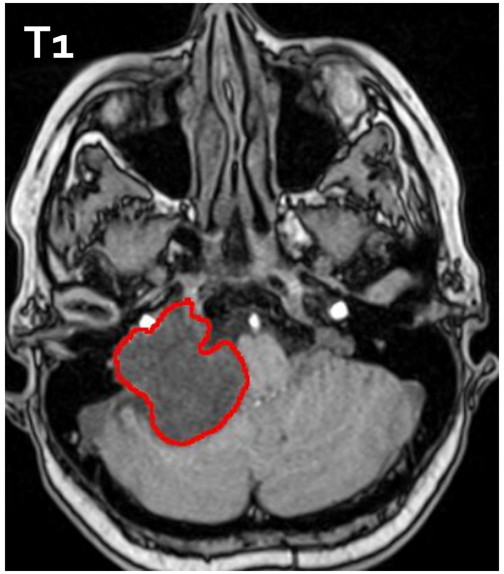
26% male. Median age – 58, IQR – [50; 64] years.

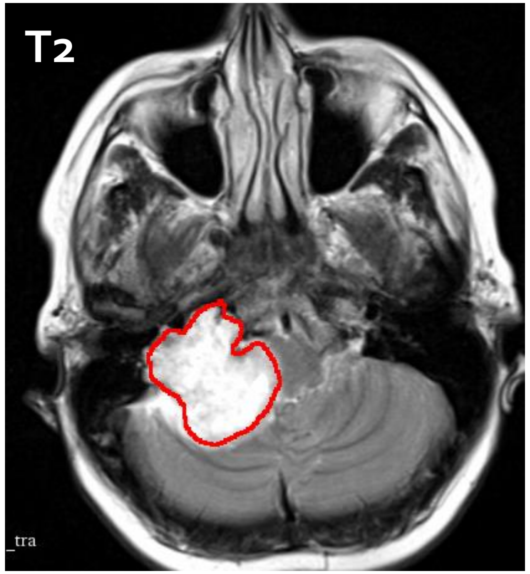
The annotations comprise the labels of the peritumoral edema (yellow), the non-enhancing tumor (blue), GD-enhancing tumor (red), and the necrotic tumor core (green).

Neurinomas (130)





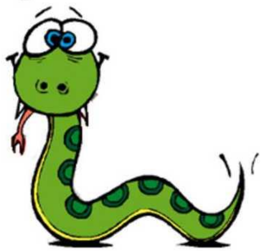




32% male. Median age – 53, IQR – [40; 59] years.

The annotations comprise the labels of the peritumoral edema (yellow), the non-enhancing tumor (blue), GD-enhancing tumor (red), and the necrotic tumor core (green).

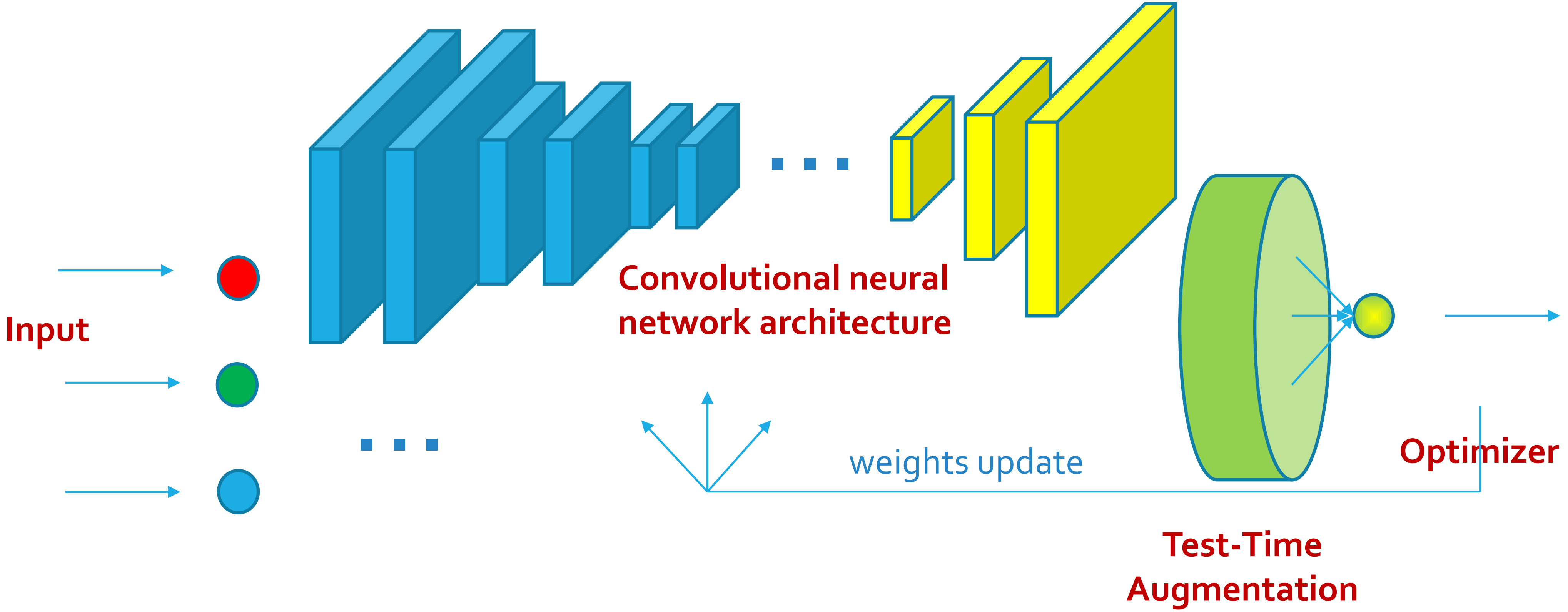
Methods and tools



- Programming language Python/CUDA
- Open CV, Pytorch, Keras, Tensorlow Libraries
- Modern convolutional neural network architecture – LinkNet, Unet, PSPNet, FPN
- MRI sequences mixture and their various distributions over neural network channels
- Optimizer
- Test-Time Augmentation

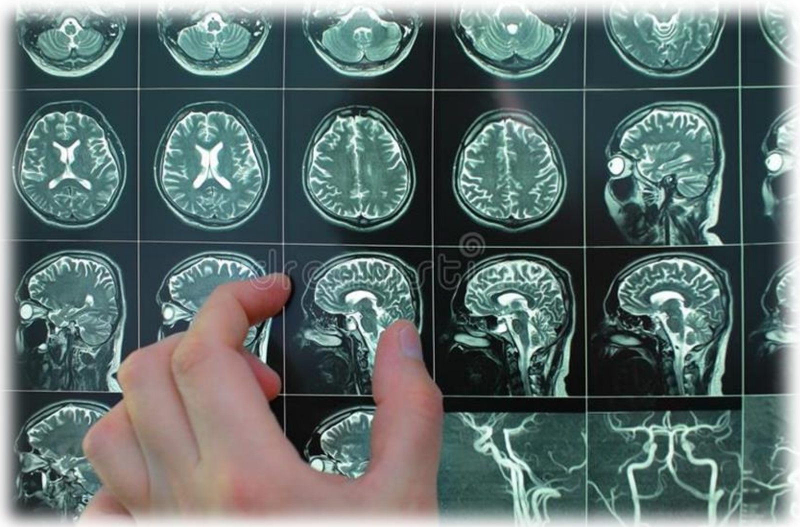
- 1 doctor of medical sciences, 2 candidates of medical sciences, 1 intern
- 1 doctor of physical-mathematical sciences, 2 candidates of physical-mathematical sciences, 1 NVidia certified specialist, 1 Ph.D. Applied Mathematics (Kaggle competitions Master) and 1 researcher in AI

Four research directions



Concerning the segmentation process with use of neural networks we chose 4 research directions.
The are marked by red color.

Input (training dataset)



The dataset consists of 100 train and 15 test brain MRI volume scans in the format of NIfTI files and totally resulting in 16270 2D slices: meningioma (30+5), neurinoma (30+5), astrocytoma (10), and glioblastoma (30+5).

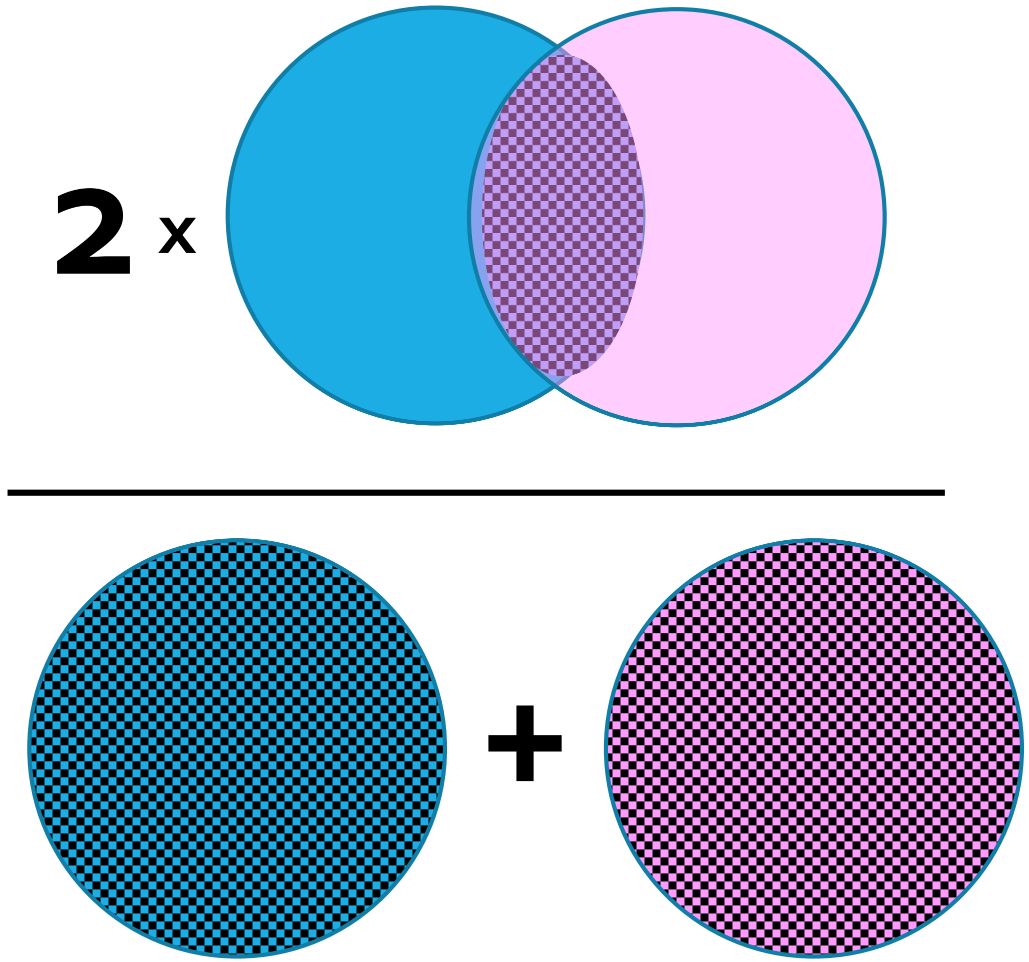
We used several approaches to define input for NN:

- combination of three neighboring slices T1-CE images as other pseudo-RGB images;
- wide input where all three sequences are used to create 9-channel input images;
- a mixture of T1, T1-CE, and T2 FLAIR sequences from the same slice in one pseudo-RGB image.

The current status: The best input (according to DICE, time, and space required by our computations) is input image by assigning each channel to each of the T1, T1-CE, and FLAIR sequences.

DICE coefficient

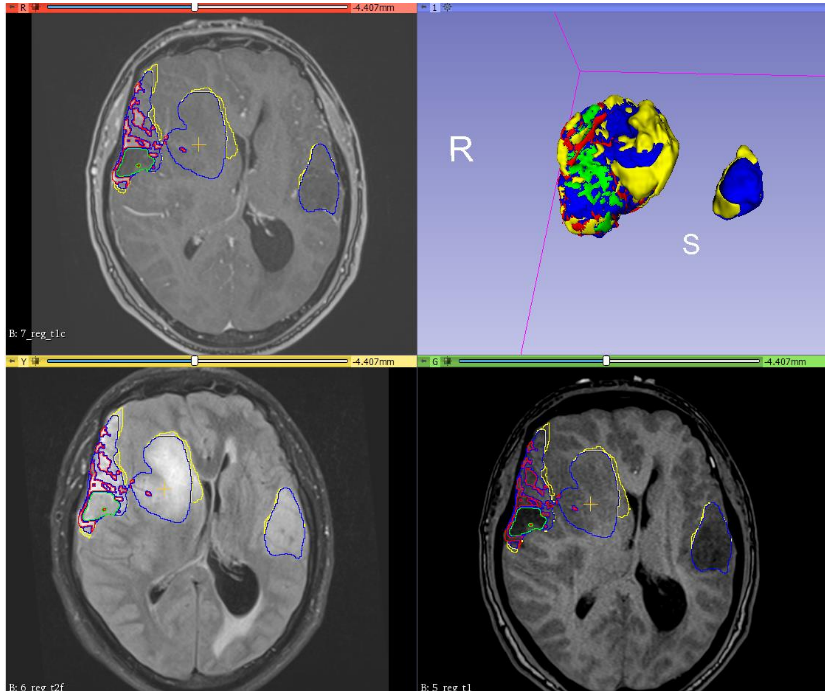
$$\text{Dice coefficient} = \frac{\text{2x area of overlapped}}{\text{total area}} =$$



Convolutional neural network architecture

Comparison of the different network architectures

Backbone	validation Dice	test Dice
PSPNet_Sx50	0.970	0.864
FPN_Sx50	0.974	0.884
LinkNet_SE154	0.984	0.918
LinkNet_Sx50	0.984	**0.927**



We used the same Se-ResNeXt- 50 32x4d encoder and appropriate decoder part which were fixed without any modifications from one experiment to another.

Optimizer

Optimizers are algorithms or methods used to change the attributes of your neural network such as weights and learning rate in order to reduce the losses.

Comparison of the different optimizers

Optimizer	validation Dice	test Dice
Adam	0.983	0.920
Radam	0.983	0.922
Ranger	0.983	0.921
Ralamb	0.984	**0.927**

This comparison was done on a single fold with all absolutely fixed parameters of the training setup.
Here Ralamb is the modification of Adam with the Look Ahead method.
Moreover, we can observe that Ralamb optimizer leads to faster convergence compared to other methods.

Test-Time Augmentation

Test-time augmentation is an application of data augmentation to the test dataset. It involves creating multiple augmented copies of each image in the test set, having the model make a prediction for each, then returning an ensemble of those predictions.

Impact of TTA on the model performance based on the test and hold out sets

Model	Test Dice	Hold out Dice
Sx50_ensemble	0.9491	0.9547
Sx50_ensemble_TTA1	0.9498	0.9558
Sx50_ensemble_TTA2	0.9512	0.9568
Sx50_ensemble_TTA3	0.9527	0.9591

These results include the comparison of 3 different types of TTA, where TTA1 stays for the averaging of the original input image and its horizontal flip; TTA2 - original, horizontal flip, vertical flip and sequential horizontal and vertical flip; TTA3 - full set of D4 group transformations, including also rotations of 90, 180 and 270 degrees.

***BUT** Analysis for different tumors showed that neurinomas segmentations were the best with use of TTA2.*

Conclusions

- **The dataset of 4 tumors type and 500 cases was created**. It includes a complete clinical diagnosis, a detailed description of pathological manifestations, protocols of operations, data on the postoperative course with histology and immunohistochemical examination.
- We developed and implemented protocols for **manual and automatic segmentation of MRI images in the DICOM format approved by two independent expert radiologists**.
- The modern convolutional neural network architectures were used for the automatic markup protocol. We achieved **the segmentation quality according to the Dice metric at the level of 95%** on the test sample, that corresponds to the radiologist expert level.

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Thank you for attention!

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