

Nr.	Autor(i)/ an	Titlul articolului/proiectului	Aplicație/ domeniu	Tehnologii utilizate	Metodologie/ abordare	Rezultate	Limitări	Comentarii suplimentare
1.	Benjamin Billot; Douglas N. Greve; Koen Van Leemput; Bruce Fischl; Juan Eugenio Iglesias; Adrian V. Dalca; - 8 Apr 2021 -	A Learning Strategy for Contrast-agnostic MRI Segmentation	Medical	GPU Nvidia P6000 (SynthSeg), Intel Xeon (Samseng)	Supervised, SAMSEG, SynthSeg-rule, SynthSeg	Fig.1	Limitare a setului de date	Strategie: SynthSeg – permite segmentarea automata a scanarilor cerebrale nepreprocesat e a oricarui contrast RMN
2.	Dinthisrang Daimary, Mayur Bhargab Bora, Khwaieakpam Amitab, Debdatta Kandar -2019-	Brain Tumor Segmentation from MRI Images using Hybrid Convolutional Neural Networks	Medical	Decoder, Codificator	U-Net, SegNet, ResNet18	Fig.2	Timp de calcul mare	
3.	Jason Walsh, Alice Othmani, Mayank Jain, Soumyabrata Dev - 3 noi. 2022 -	Using U-Net Network for Efficient Brain Tumor Segmentation in MRI Images	Medical	TensorFlow	Thresholding, K-Means, Fuzzy C, LinkNet, U- Net	Fig.3	-	Mai multe tipuri de strategii
4.	Ali Hatamizadeh, Vishwesh Nath, Yucheng Tang, Dong Yang, Holger R. Roth,	Swin Transformers for Semantic Segmentation of Brain Tumors in MRI Images	Medical	Decoder, GPU NVIDIA V100, Dice loss, PyTorch, MONAI	Swin UNETR	Fig.4	-	Metodologia este considerata printre cele mai bune

	Daguan Xu - 4 ian. 2022 -							
5.	Ayan Gupta, Mayank Dixit, Vipul Kumar Mishra, Attylya Singh, Atul Dayal	Brain Tumor Segmentation from MRI Images using Deep Learning Techniques	Medical	Matlab, GPU NVIDIA TESLA P100 cu 2 nuclee CPU	U-Net, ResUnet, ResUnet++	Fig. 5	Imaginile acceptate doar in format „png”.	Spre deosebire de celelalte analize, utilizeaza optimizatorul Adam

Segmentarea tumorilor cerebrale prin imagini RMN

Method	Overall performance		modality-agnostic	runtime (s)
Supervised	0.89 ± 0.10 (same dataset)		No	3.06 ± 0.02
SAMSEG	0.83 ± 0.02		Yes	1382 ± 192
SynthSeg-rule	0.82 ± 0.02		Yes	3.22 ± 0.03
SynthSeg	0.85 ± 0.02		Yes	3.22 ± 0.03

Fig.1

Table 1. Segmentation performance of the CNN models.

Model name	Global accuracy	Mean accuracy	Mean IOU	Weighted IOU	Mean BF-score
SegNet3	0.97628	0.89327	0.53646	0.95859	0.77267
SegNet5	0.98194	0.91787	0.60213	0.98567	0.64461
U-Net	0.98085	0.90425	0.59213	0.97567	0.63499
U-SegNet	0.9824	0.91689	0.64791	0.98221	0.8451
Res-SegNet	0.98854	0.93352	0.68914	0.98293	0.82147
Seg-UNet	0.99117	0.93124	0.73409	0.986357	0.85078

Fig.2

Table 3: Comparison of the results obtained during the benchmarking process.

Method	Pixel Acc (%)	Mean Acc (%)	Mean IoU (%)	FWIoU (%)
Coronal				
Thresholding	91	70	47	90
K-Means	79	72	41	78
Fuzzy C	84	73	44	83
LinkNet	99	78	76	99
U-Net	99	88	84	99
Sagittal				
Thresholding	93	58	48	92
K-Means	82	60	42	81
Fuzzy C	86	56	44	85
LinkNet	99	60	59	98
U-Net	99	76	75	99
Transversal				
Thresholding	97	59	51	96
K-Means	91	67	48	90
Fuzzy C	91	70	48	91
LinkNet	99	83	81	99
U-Net	99	85	84	99
Full				
Thresholding	95	61	49	93
K-Means	86	65	45	85
Fuzzy C	88	65	45	87
LinkNet	99	87	84	99
U-Net	99	91	89	99

Fig.3

Validation dataset	Dice			Hausdorff (mm)		
	ET	WT	TC	ET	WT	TC
Swin UNETR	0.858	0.926	0.885	6.016	5.831	3.770

Fig. 4

Table 3. Statistical results of various state-of-art deep learning models for tumor segmentation

Methodologies	F1 Score	Mean IoU
UNET (VGG-19 backbone)	0.8033	0.8322
UNET (ResNet152 backbone)	0.8116	0.8382
UNET (Densenet201 backbone)	0.8288	0.8507
Attention UNET (VGG-19 backbone)	0.8060	0.8342
Attention UNET (ResNet152 backbone)	0.8188	0.8434
Attention UNET (Densenet201 backbone)	0.8349	0.8553
ResUnet	0.8360	0.8562
ResUnet++	0.7969	0.8272
Recurrent Residual UNET	0.8495	0.8665

Fig.5

Webografie:

- <https://arxiv.org/pdf/2305.00257>
- <https://arxiv.org/pdf/2201.01266v1>
- https://www.sciencedirect.com/science/article/pii/S1877050920307614?ref=pdf_download&fr=RR-2&rr=8de77c25e811c9e1
- <https://arxiv.org/pdf/2211.01885>
- <https://arxiv.org/pdf/2003.01995v3>