UNETR: TRANSFORMERS FOR 3D MEDICAL IMAGE SEGMENTATION

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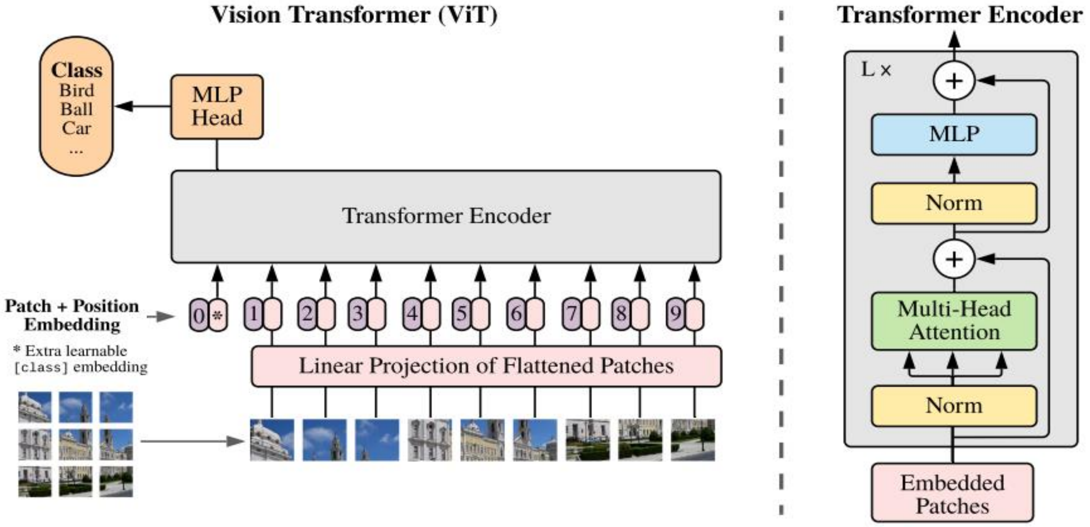
MONAI Bootcamp – September 22 , 2021

MOTIVATION

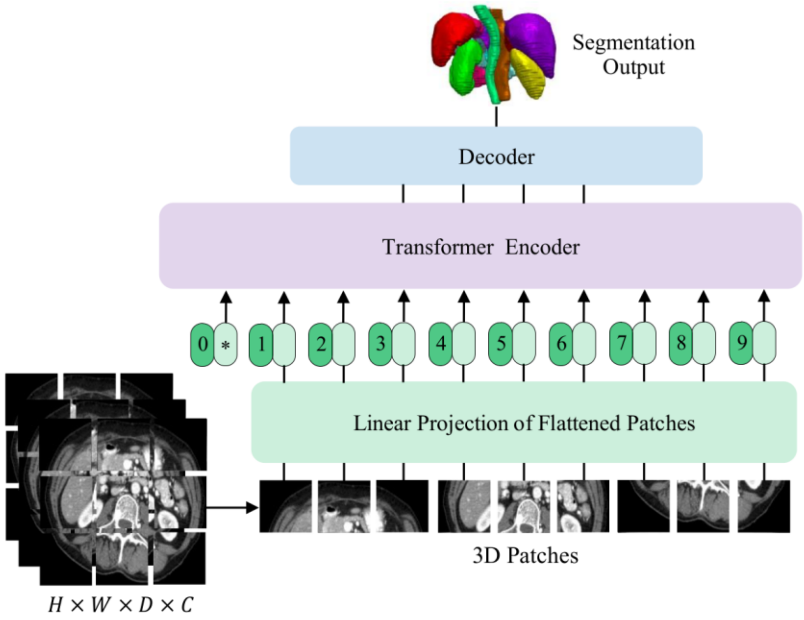
- Transformer-based models have started a revolution in NLP and computer vision due to:
  - Their exceptional capability in learning pre-text tasks
  - Scalability for large-scale training
  - Good performance in modeling long-range spatial dependencies



Vision Transformer (Dosovitskiy et al. [1])

MOTIVATION

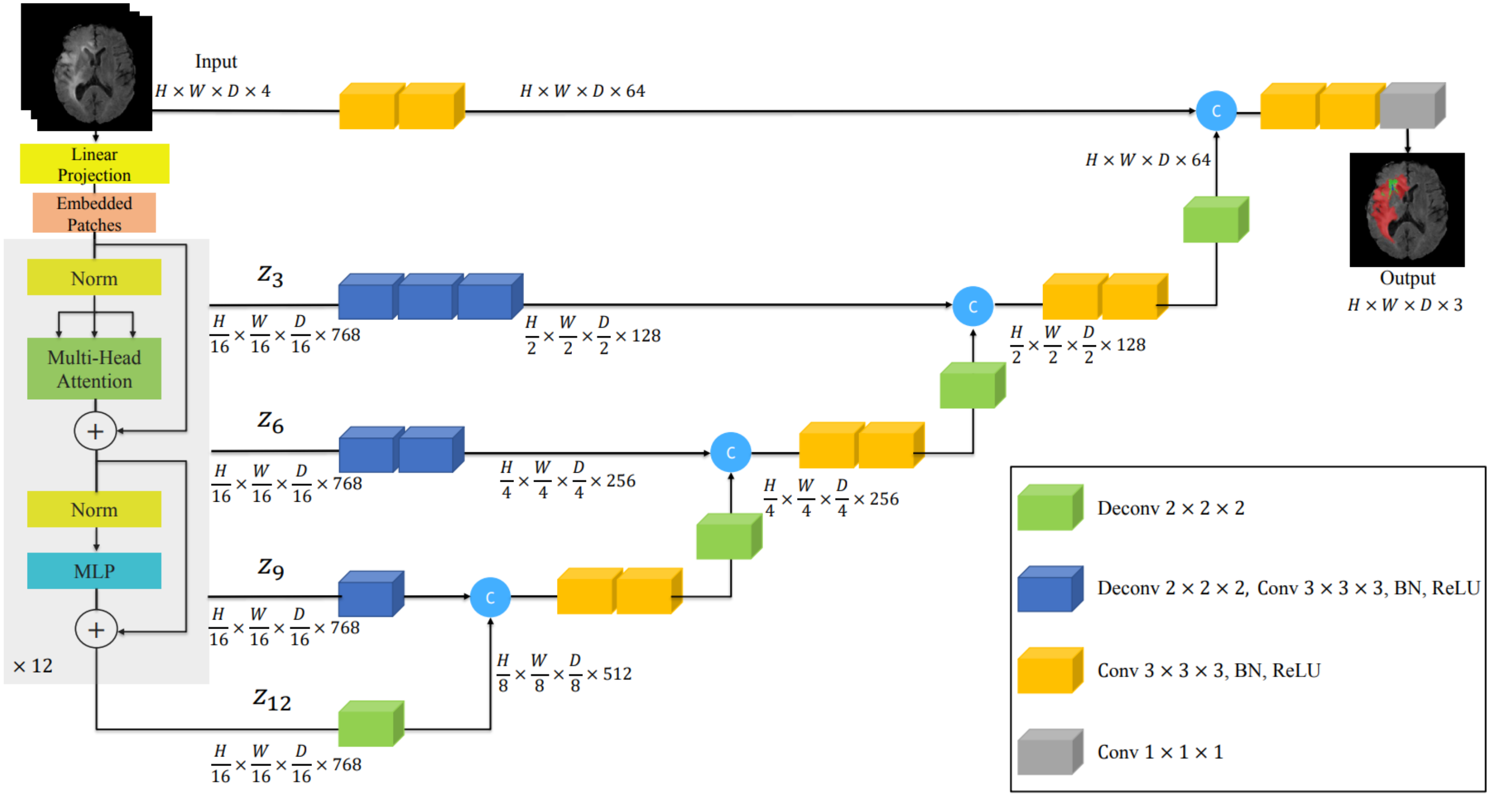
- We propose UNEt TRansformers (UNETR) which reformulates the task of 3D segmentation as 1D sequence-to-sequence prediction task:
  - Uses self-attention modules to learn weighted sum of values calculated from hidden layers
  - Achieves state-of-the-art performance on multi-organ segmentation Synapse public leaderboard



UNETR (Hatamizadeh et al. [2])

METHODOLOGY

- UNETR uses a vision transformer backbone and propose to use a CNN-based decoder in a UNET-like segmentation framework.



UNETR (Hatamizadeh et al. [2])

METHODOLOGY

- UNETR directly utilizes 3D multi-channel inputs $\mathbf{x} \in \mathbb{R}^{H\times W\times D\times C}$, divides them into non-overlapping patches $\mathbf{x}_v \in \mathbb{R}^{N\times(P^3.C)}$ with resolution P, projects the flattened patches into a K-dimentional embedding space and adds a learnable positional encoding layer to preserve the spatial information:

$$\mathbf{z}_0 = [\mathbf{x}_v^1\mathbf{E}; \mathbf{x}_v^2\mathbf{E}; ...; \mathbf{x}_v^N\mathbf{E}] + \mathbf{E}_{pos}$$

- UNETR employs transformer blocks comprising of multi-head self-attention (MSA) and multilayer perceptron (MLP) sublayers :

$$\mathbf{z}'_i = \mathrm{MSA}(\mathrm{Norm}(\mathbf{z}_{i-1})) + \mathbf{z}_{i-1}, \quad i = 1...L,$$

$$\mathbf{z}_i = \mathrm{MLP}(\mathrm{Norm}(\mathbf{z}'_i)) + \mathbf{z}'_i, \quad i = 1...L,$$

METHODOLOGY

- A MSA sublayer comprises of n parallel self-attention (SA) heads.
- The SA block, is a parameterized function that learns the mapping between a query (q) and the corresponding key (k) and value (v) representations in a sequence (z).
- The attention weights are computed by measuring the similarity between two elements in z and their key-value pairs according to

$$\mathrm{A} = \mathrm{Softmax}\left(\frac{\mathbf{q}\mathbf{k}^{\top}}{\sqrt{K_h}}\right)$$

- Using the computed attention weights, the output of SA for values v in the sequence z and output of MSA block are computed according to

$$\mathrm{SA}(\mathbf{z}) = \mathbf{A}\mathbf{v}$$

$$\mathrm{MSA}(\mathbf{z}) = [\mathrm{SA}_1(\mathbf{z}); \mathrm{SA}_2(\mathbf{z}); \ldots; \mathrm{SA}_n(\mathbf{z})]\mathbf{W}_{msa}$$

QUANTITATIVE RESULTS

- UNETR model is the current state-of-the-art on BTCV public leaderboard

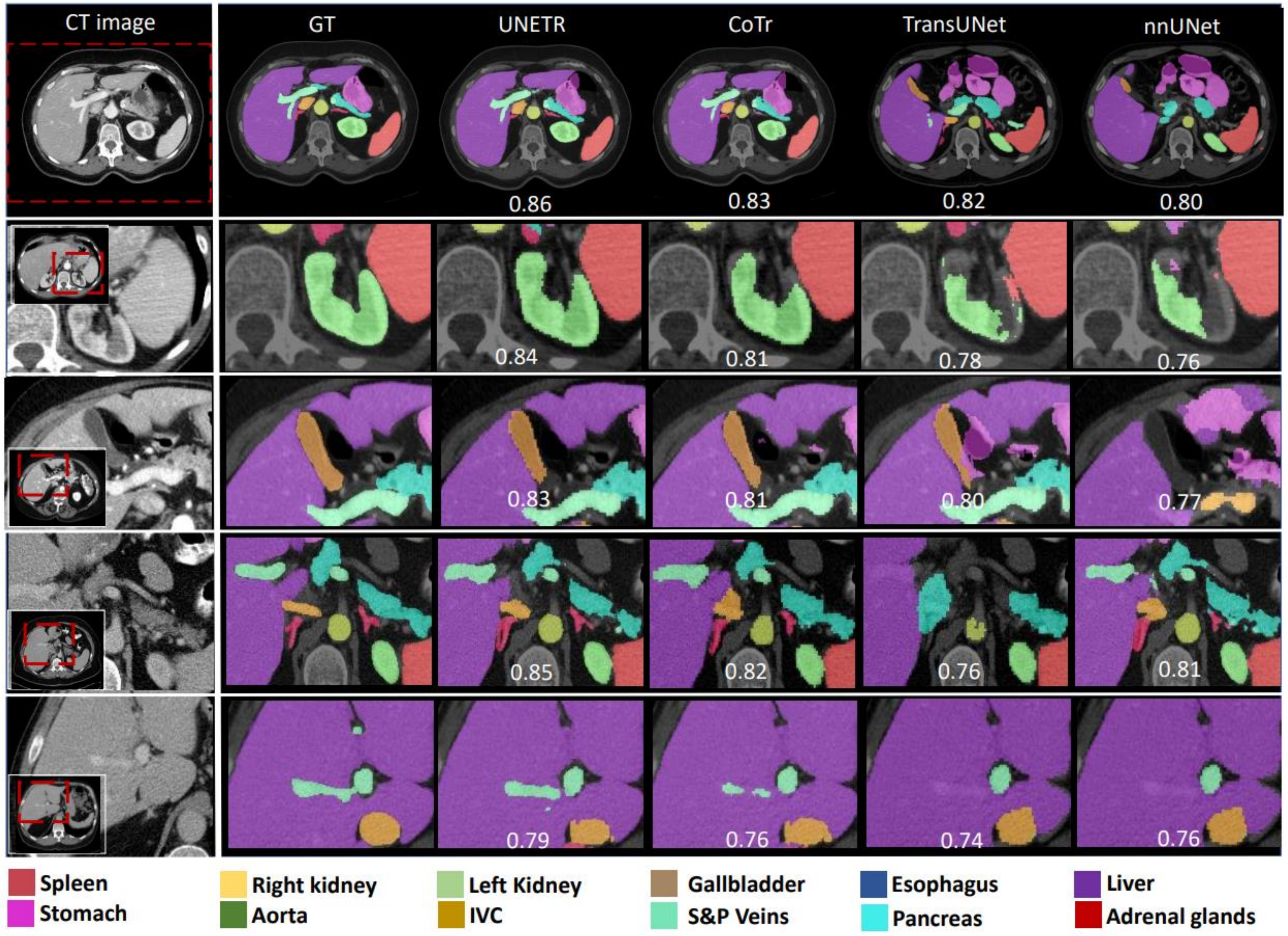
Methods	Spl	RKid	LKid	Gall	Eso	Liv	Sto	Aor	IVC	Veins	Pan	AG	Avg.
SETR NUP [53]	0.931	0.890	0.897	0.652	0.760	0.952	0.809	0.867	0.745	0.717	0.719	0.620	0.796
SETR PUP [53]	0.929	0.893	0.892	0.649	0.764	0.954	0.822	0.869	0.742	0.715	0.714	0.618	0.797
SETR MLA [53]	0.930	0.889	0.894	0.650	0.762	0.953	0.819	0.872	0.739	0.720	0.716	0.614	0.796
nnUNet [21]	0.942	0.894	0.910	0.704	0.723	0.948	0.824	0.877	0.782	0.720	0.680	0.616	0.802
ASPP [10]	0.935	0.892	0.914	0.689	0.760	0.953	0.812	0.918	0.807	0.695	0.720	0.629	0.811
TransUNet [7]	0.952	**0.927**	0.929	0.662	0.757	0.969	0.889	0.920	0.833	0.791	0.775	0.637	0.838
CoTr w/o CNN encoder [48]	0.941	0.894	0.909	0.705	0.723	0.948	0.815	0.876	0.784	0.723	0.671	0.623	0.801
CoTr* [48]	0.943	0.924	0.929	0.687	0.762	0.962	0.894	0.914	0.838	**0.796**	**0.783**	0.647	0.841
CoTr [48]	0.958	0.921	0.936	0.700	0.764	0.963	0.854	**0.920**	0.838	0.787	0.775	0.694	0.844
UNETR	**0.968**	0.924	**0.941**	**0.750**	**0.766**	**0.971**	**0.913**	0.890	**0.847**	0.788	0.767	**0.741**	**0.856**
RandomPatch [40]	0.963	0.912	0.921	0.749	0.760	0.962	0.870	0.889	0.846	0.786	0.762	0.712	0.844
PaNN [54]	0.966	0.927	0.952	0.732	0.791	0.973	0.891	0.914	0.850	0.805	0.802	0.652	0.854
nnUNet-v2 [21]	0.972	0.924	**0.958**	0.780	0.841	0.976	0.922	0.921	0.872	0.831	0.842	0.775	0.884
nnUNet-dys3 [21]	0.967	0.924	0.957	**0.814**	0.832	0.975	0.925	0.928	0.870	0.832	**0.849**	0.784	0.888
UNETR	**0.976**	**0.942**	0.953	**0.814**	**0.889**	**0.979**	**0.941**	**0.947**	**0.886**	**0.858**	0.823	**0.786**	**0.899**

QUANTITATIVE RESULTS

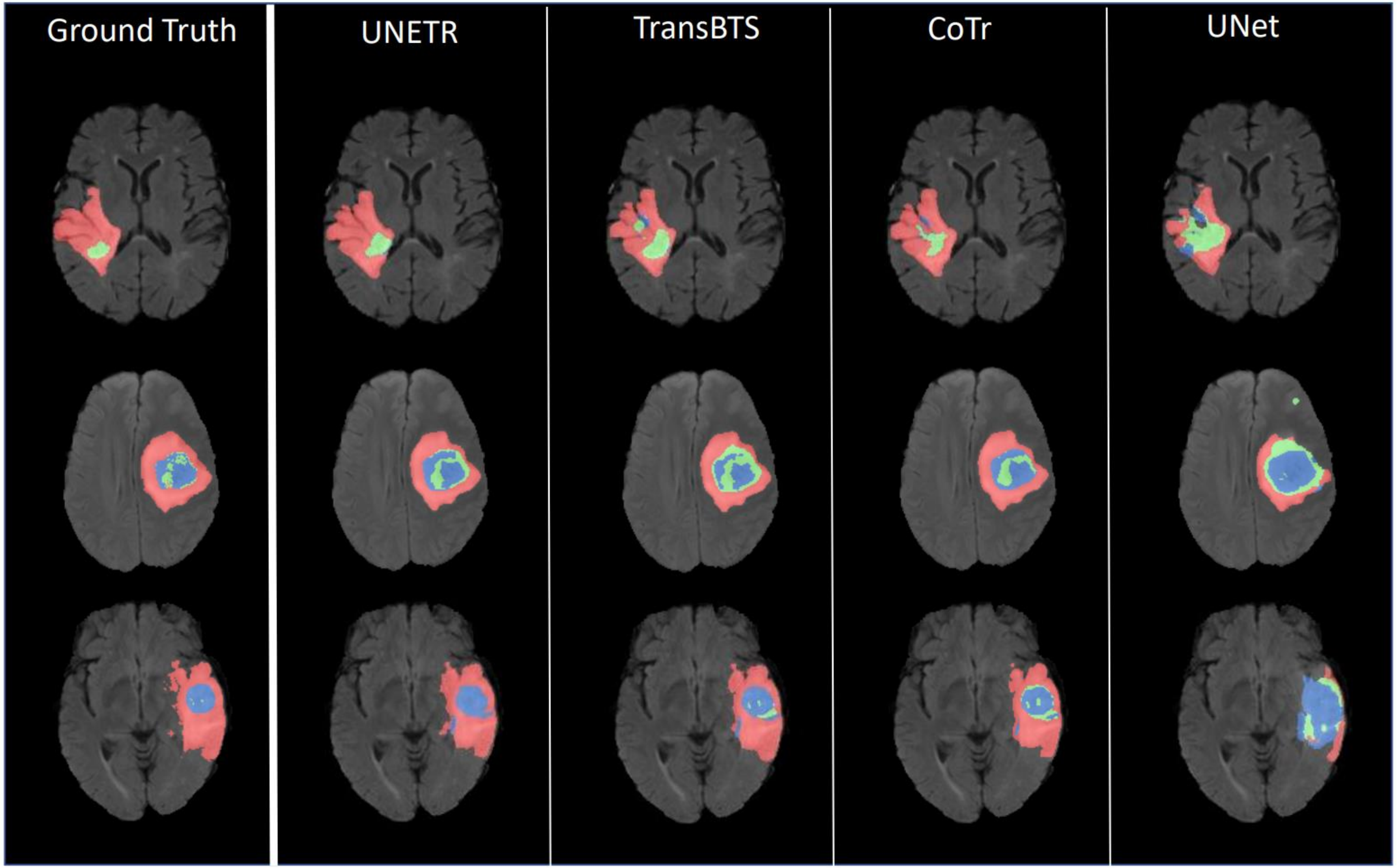
- UNETR model achives competetive performance on brain tumor and spleen segmentation task on MSD dataset.

Task/Modality	Spleen Segmentation (CT)		Brain tumor Segmentation (MRI)							
Anatomy	Spleen		WT		ET		TC		All	
Metrics	Dice	HD95	Dice	HD95	Dice	HD95	Dice	HD95	Dice	HD95
UNet [36]	0.953	4.087	0.766	9.205	0.561	11.122	0.665	10.243	0.664	10.190
AttUNet [34]	0.951	4.091	0.767	9.004	0.543	10.447	0.683	10.463	0.665	9.971
SETR NUP [53]	0.947	4.124	0.697	14.419	0.544	11.723	0.669	15.192	0.637	13.778
SETR PUP [53]	0.949	4.107	0.696	15.245	0.549	11.759	0.670	15.023	0.638	14.009
SETR MLA [53]	0.950	4.091	0.698	15.503	0.554	10.237	0.665	14.716	0.639	13.485
TransUNet [7]	0.950	4.031	0.706	14.027	0.542	10.421	0.684	14.501	0.644	12.983
TransBTS [44]	-	-	0.779	10.030	0.574	9.969	0.735	8.950	0.696	9.650
CoTr w/o CNN encoder [48]	0.946	4.748	0.712	11.492	0.523	9.592	0.698	12.581	0.6444	11.221
CoTr [48]	0.954	3.860	0.746	9.198	0.557	9.447	0.748	10.445	0.683	9.697
UNETR	**0.964**	**1.333**	**0.789**	**8.266**	**0.585**	**9.354**	**0.761**	**8.845**	**0.711**	**8.822**

QUALITATIVE RESULTS



QUALITATIVE RESULTS



MODEL COMPLEXITY

- Comparison of number of parameters, FLOPs and averaged inference time for various models in BTCV experiments.

Models	#Params (M)	FLOPs (G)	Inference Time (s)
nnUNet [21]	19.07	412.65	10.28
CoTr [48]	46.51	399.21	19.21
TransUNet [7]	96.07	48.34	26.97
ASPP [11]	47.92	44.87	25.47
SETR [53]	86.03	43.49	24.86
UNETR	92.58	41.19	12.08

CONCLUSION

- In this work, we have proposed a novel transformer-based segmentation network dubbed as UNETR for medical imaging semantic segmentation
- Our proposed UNETR is the current state-of-the-art on BTCV public leaderboard for the task of multi-organ semantic segmentation. UNETR also achieves competetive performance on spleen and brains segmentation tasks using MSD dataset.
- Our work paves the way for a new class of transformer-based networks for medical image segmentation.
- UNETR is currently available as part of MONAI:
  - Repository: https://monai.io/research/unetr
  - Tutorial: https://github.com/Project-MONAI/tutorials/blob/master/3d_segmentation/unetr_btcv_segmentation_3d.ipynb
  - Paper: https://arxiv.org/abs/2103.10504

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2. Hatamizadeh, A., Tang, Y., Nath, V., Yang, D., Myronenko, A., Landman, B., Roth, H., and Xu, D., 2021, August. UNETR: Transformers for 3D Medical Image Segmentation. *arXiv preprint arXiv:2103.10504* (2021).

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