Evidence fusion with contextual discounting for multi-modality medical image segmentation

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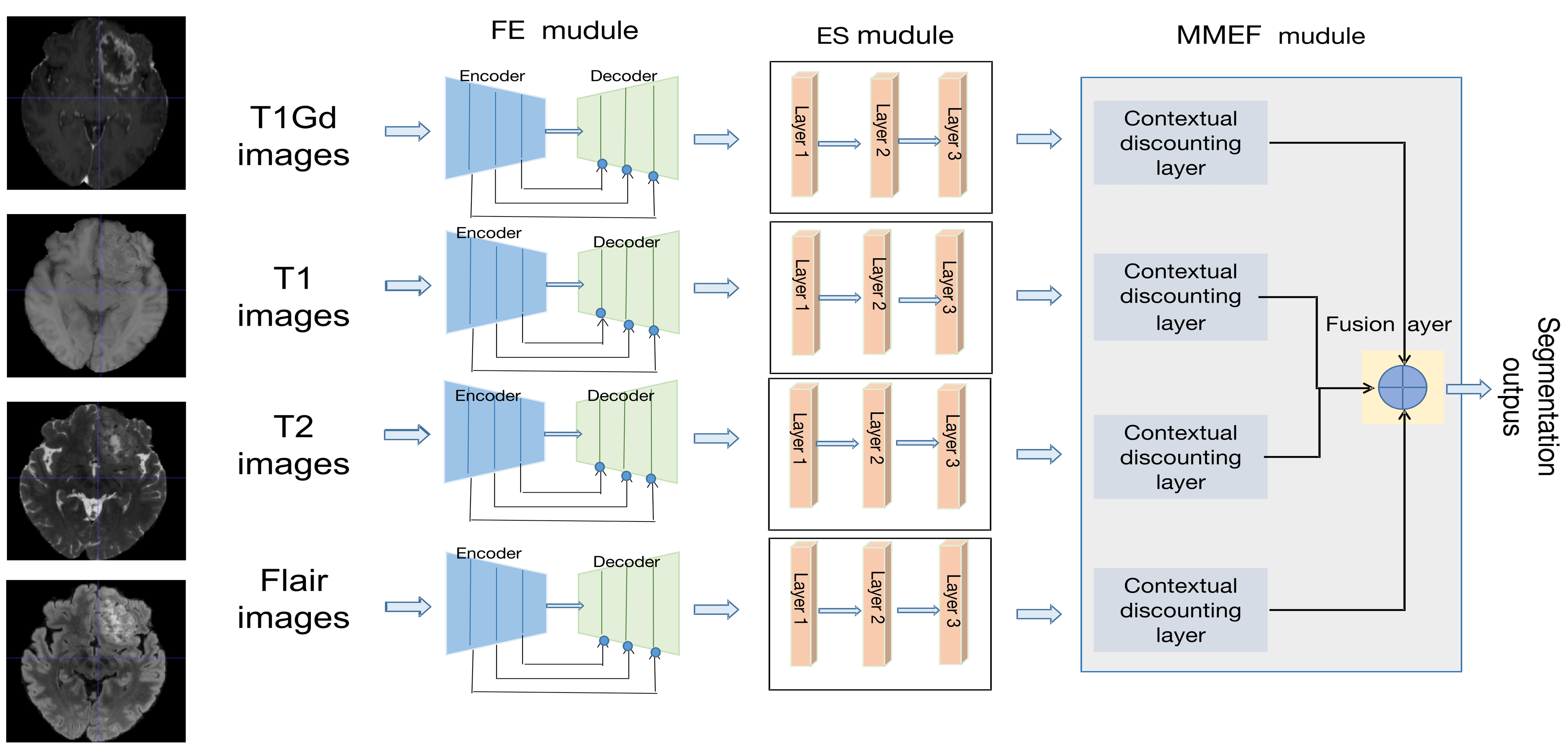
BACKGROUND

- In clinical treatment, single-modality biomedical data have limitations in expressing disease information completely.
- The fusion of multiple information is vital to improving the diagnosis accuracy.

CONTRIBUTIONS

- A multi-modality evidence fusion framework considering uncertainty and reliability is proposed;
- Four evidential segmentation modules compute the belief of each voxel belonging to the tumor and the corresponding uncertainty;
- An evidence-discounting mechanism [1] is applied to account model's realibility;
- A multi-modality evidence fusion strategy is applied to combine the discounted evidence.

METHOD



(1) Evidential segmentation

The ES module assigns a mass to each of the K classes and to the whole set of classes Ω, based on the distance between the feature vector x and prototype centers p.

$$m_i(\{\omega_k\}) = \mu_{ik}\, \alpha_i\, exp(-\gamma_i \|x - p_i\|),\ k = 1, \ldots K,$$

$$m_i(\Omega) = 1 - \alpha_i\, exp\text{-}\gamma_i \|x - p_i\|)\ .$$

(2) Multi-modality evidence fusion

Contextual discounting. We introduce a vector $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_K)$ for each modality input, where β_k is the degree of belief that the source is reliable given that the true class is ω_k.

$$^{\beta}pl(\{\omega_k\}) = 1\text{-}\beta_k + \beta_k\, pl(\{\omega_k\}),\ k=1,\ldots,K,$$

$$pl\ (\{\omega_k\}) = m_i(\{\omega_k\}) + m_i(\Omega)\ .$$

Evidence fusion. The discounted evidnece is fused by Dempster's rule.

RESULTS

Table 1. Segmentation Results on BraTS 2021 dataset

Methods	Dice score				Hausdorff distance			
	ET	TC	WT	Avg	ET	TC	WT	Avg
UNet [3]	83.39	86.28	89.59	86.42	11.49	6.18	6.15	7.94
VNet [18]	81.04	84.71	90.32	85.36	17.20	7.48	7.53	10.73
nnFormer [22]	82.83	86.48	90.37	86.56	11.66	7.89	8.00	9.18
VT-UNet [19]	85.59	87.41	91.20	88.07	**10.03**	6.29	6.23	7.52
Residual-UNet [15]	85.07	87.61	89.78	87.48	11.76	6.14	6.31	8.07
nnUNet [13]	87.12	**90.31**	91.47	89.68	12.46	11.04	5.97	9.82
MMEF-UNet (Ours)	86.96	87.46	90.68	88.36	10.20	**6.07**	5.29	**7.18**
MMEF-nnUNet (Ours)	**87.26**	90.05	**92.83**	**90.04**	10.09	9.68	**5.10**	8.29

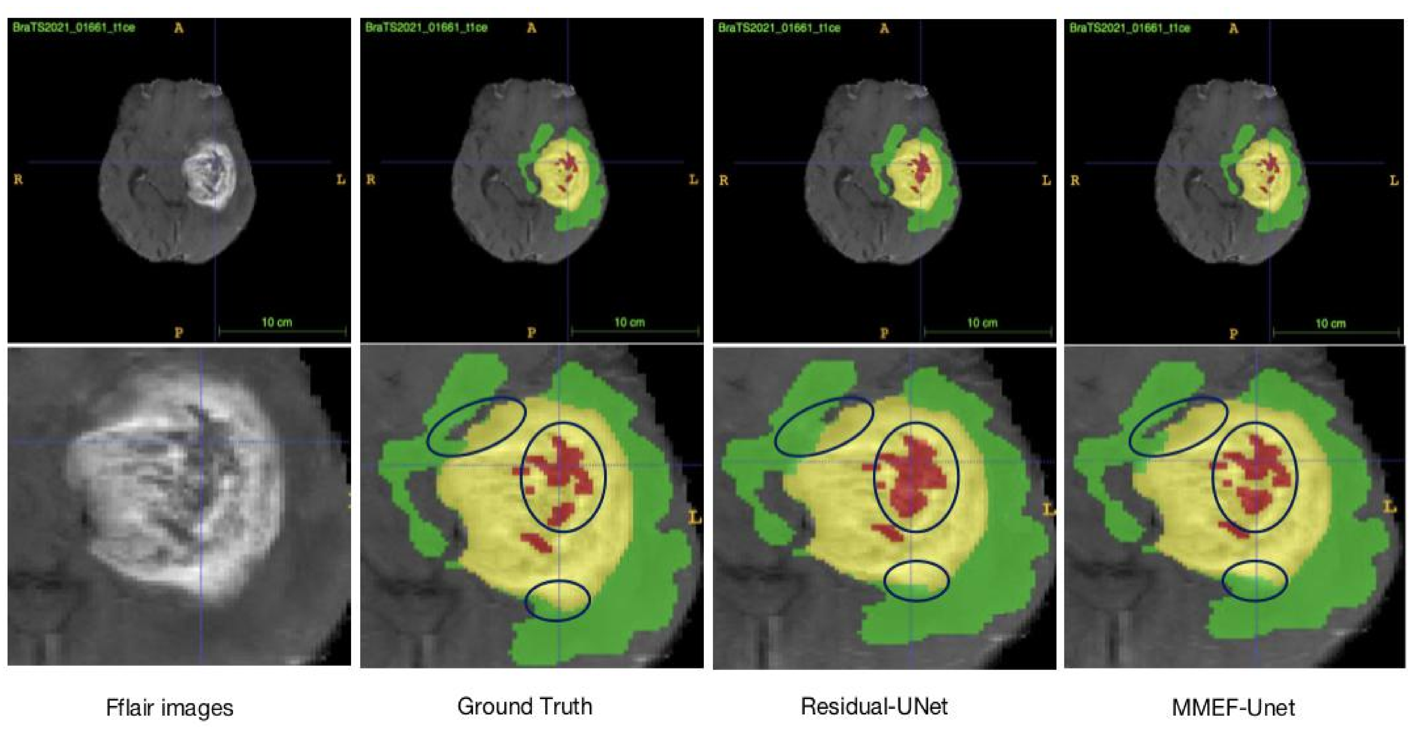


Figure 1. Visualized segmentation results.

Table 2. Reliability value β (after training) for classes ET, ED and NRC/NET and the four modalities

β	ET	ED	NRC/NET
T1Gd	0.9996	0.9726	0.9998
T1	0.4900	0.0401	0.2655
T2	0.4814	0.3881	0.4563
Flair	0.0748	0.86207	0.07512

CONCLUSIONS

- This work is the first to implement contextual discounting for the fusion of multi-modal information with DNN.
- The limitations of this work remain in the computation cost and segmentation accuracy.

REFERENCES

[1] Mercier, David, Benjamin Quost, and Thierry Denœux. "Refined modeling of sensor reliability in the belief function framework using contextual discounting." Information fusion 9.2 (2008): 246-258.

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