

RS-Net: Regression-Segmentation 3D CNN for Synthesis of Full Resolution Missing Brain MRI in the Presence of Tumour Intelligent Machines

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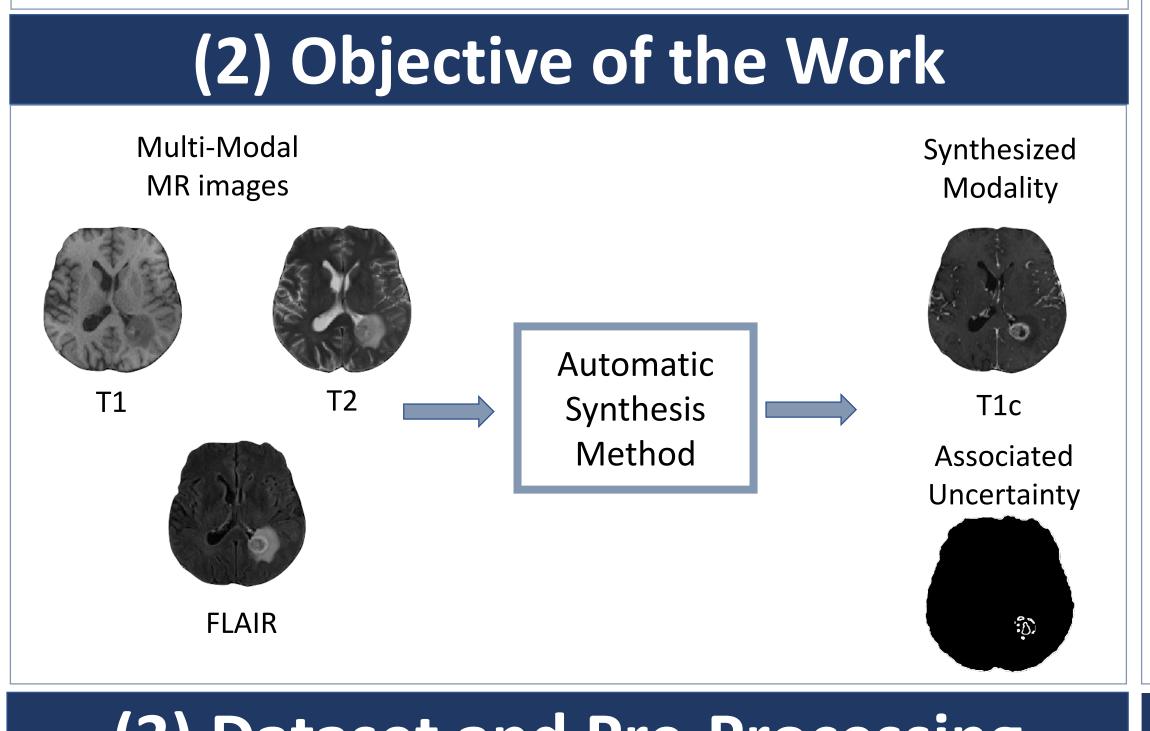
#### (1) Introduction

- Multi-modal magnetic resonance images (MRI) improves analysis of neurological diseases such as brain tumours.
- Not all required MRI sequences will be reliably available in real clinical contexts due to:
  - Cost or time constraints
  - Corruption due to noise
  - Patient motion, etc.
- of the tumour. In order to use them reliably, should quantify

Automatic synthesis of MRI sequence from available

sequences would be very helpful – particularly in area

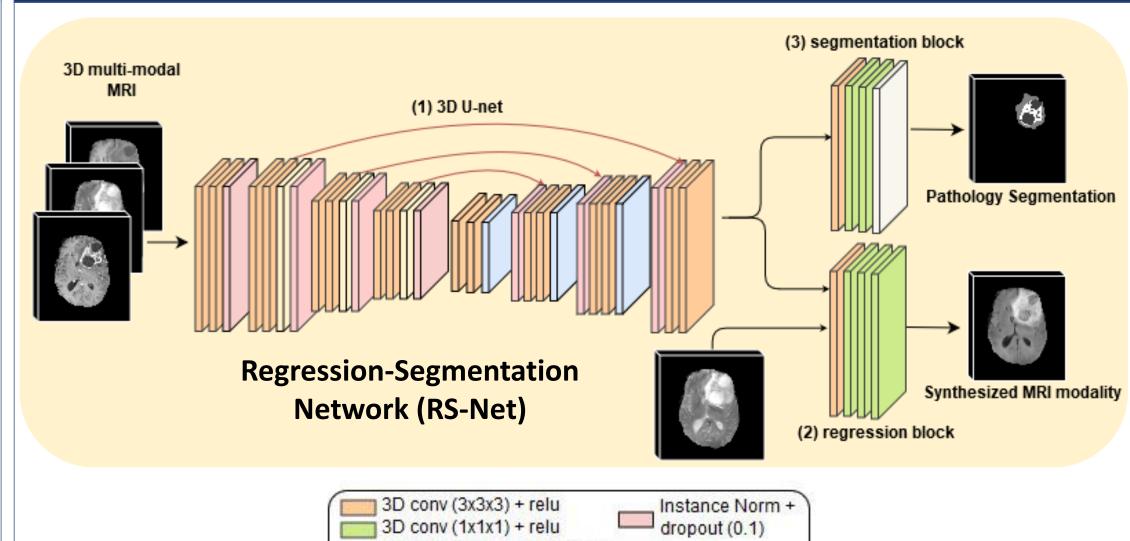
confidence in the synthesized MRI.



# (3) Dataset and Pre-Processing

- BraTS 2017 Dataset
- Training Set: 210 HGG and 75 LGG patients
- Validation Set: 46 patients
- BraTS Training set: train (228) and validate (57) network.
- BraTS Validation set: test network
- BraTS challenge provides isotropic, skull-stripped, and co-registered MR volumes (T1, T2, FLAIR, T1c)
- Manual labels for tumour sub-types: Edema, Necrotic core, and Enhancing Tumour.
- Pre-processing: Intensity Standardization using the mean and standard deviation over the masked region of a given MR image

# (4) Proposed Method



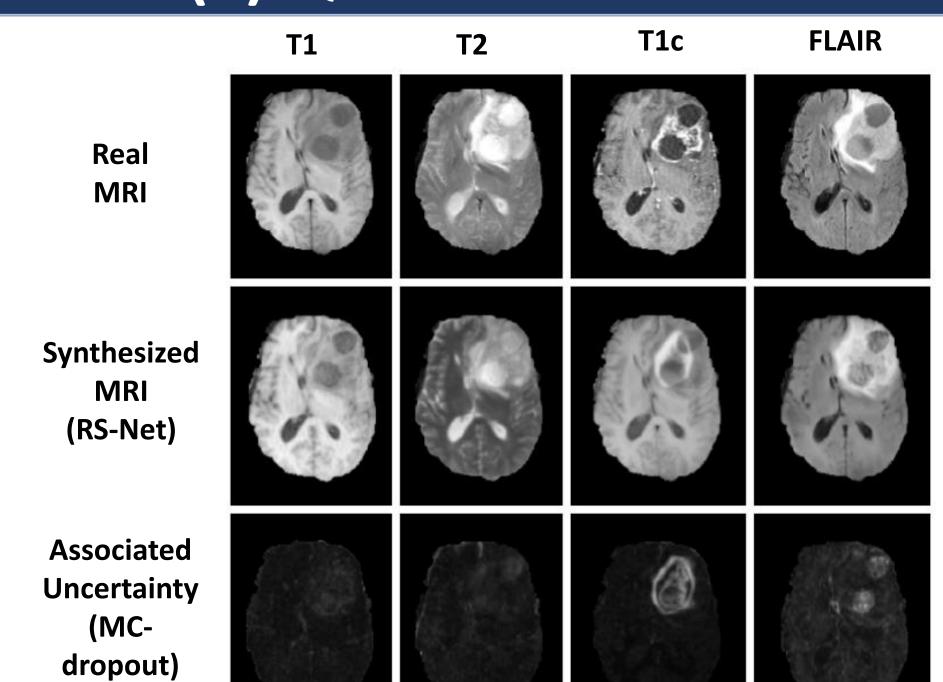
### (5) Qualitative Results

skip connection

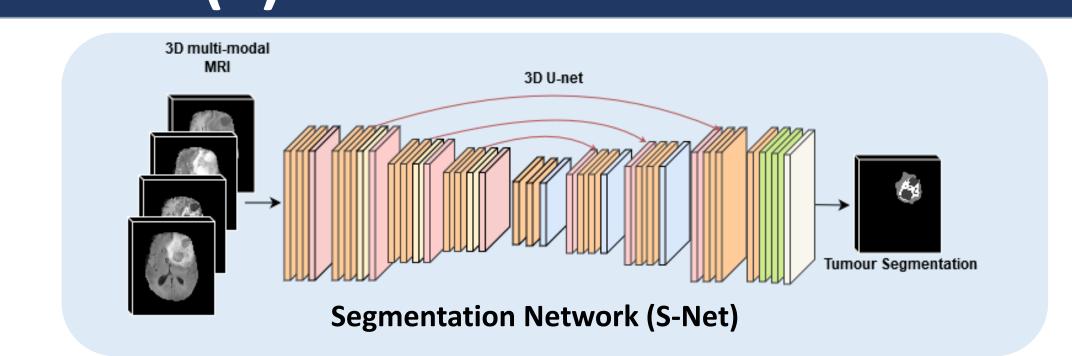
3D conv (1x1x1) + softmax

3Dtransposed conv (5x5x5)

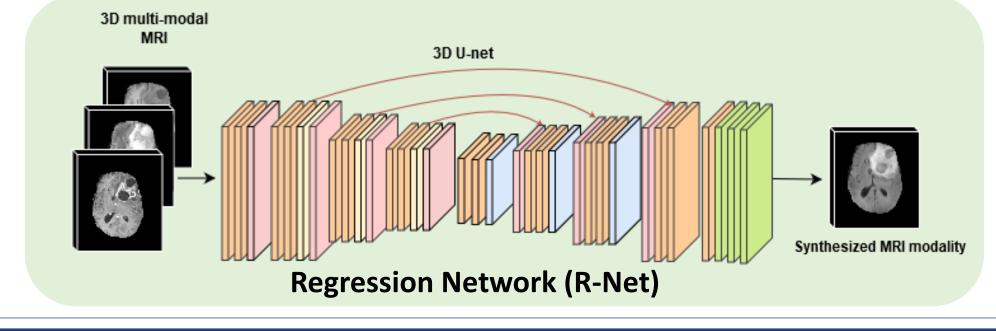
3D Maxpool (2x2x2)



## (6) Evaluation Network



# (7) Baseline Network for Comparison



# (8) Quantitative Results

- Synthesis quality based on downstream tumour segmentation task.
- Trained a segmentation network (S-Net) on Real MR Images; Replace real with synthesized (RS-Net, R-Net);
  - Objective: Minimal loss in segmentation accuracy when real image replaced with synthesized image

T1	T2	FLAIR	T1c	Dice Enhance	Dice Tumour	Dice Core
$\checkmark$	✓	✓	✓	68.2	87.9	75.7
•	✓	✓	<b>✓</b>	67.6	87.9	75.5
•	✓	$\checkmark$	<b>✓</b>	67.5	87.8	75.3
$\checkmark$	•	✓	<b>✓</b>	66.3	87.3	75.6
$\checkmark$	•	✓	<b>✓</b>	66.1	87.2	75.4
$\checkmark$	✓		<b>✓</b>	66.8	83.6	73.1
$\checkmark$	✓	•	<b>✓</b>	62.9	81.3	71.5
$\checkmark$	✓	✓		24.8	87.3	54.0
$\checkmark$	✓	✓	•	24.1	85.9	53.9
					✓ ✓ ✓ 68.2   ● ✓ ✓ 67.6   ● ✓ ✓ 67.5   ✓ ● ✓ 66.3   ✓ ✓ ✓ 66.1   ✓ ✓ 66.8   ✓ ✓ 62.9   ✓ ✓ 24.8	✓ ✓ ✓ 68.2 87.9   ● ✓ ✓ 67.6 87.9   ● ✓ ✓ 67.5 87.8   ✓ ● ✓ ✓ 66.3 87.3   ✓ ✓ ✓ 66.1 87.2   ✓ ✓ ✓ 66.8 83.6   ✓ ✓ ✓ 62.9 81.3   ✓ ✓ ✓ 24.8 87.3

Multi-class brain tumor segmentation results on the BraTS 2017 Validation Dataset. Notation: Real MRI (✓), synthesized MRI RS-Net (●), and synthesized MRI R-Net (⊙). Quantitative segmentation results based on Dice coefficients for: enhancing tumor, whole tumor, and tumor core.

# (9) Conclusion

- A full resolution 3D end-to-end CNN was developed for the task of MR volume synthesis in the presence of brain tumours
- Multi-task learning (synthesis and segmentation) helps in improving quality of synthesised MRIs
- Real MRIs can be replaced with synthesized T1, T2, and FLAIR volumes with minimum degradation in segmentation accuracy
- Synthesizing T1ce is still too challenging problem
- Uncertainty measure based on Monte Carlo dropout is helpful in communicating the confidence in the synthesis results

#### Reference: [1] Cicek et al. "3D U-Net: learning dense volumetric segmentation from sparse annotation." In

in deep learning." In ICML, pp. 1050-1059, 2016.

MICCAI, pp. 424-432. Springer, Cham, 2016. [2] Menze et al. "The multimodal brain tumor image segmentation benchmark (BRATS)." IEEE TMI 34, no. 10 (2015): 1993.

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[3] Gal and Ghahramani, "Dropout as a Bayesian approximation: Representing model uncertainty Corporation for the donation of the Titan X Pascal GPU used for this research.