IMPERIAL

MONASH University

Virtual Full-stack Scanning of Brain MRI via Imputing Any Quantised Code

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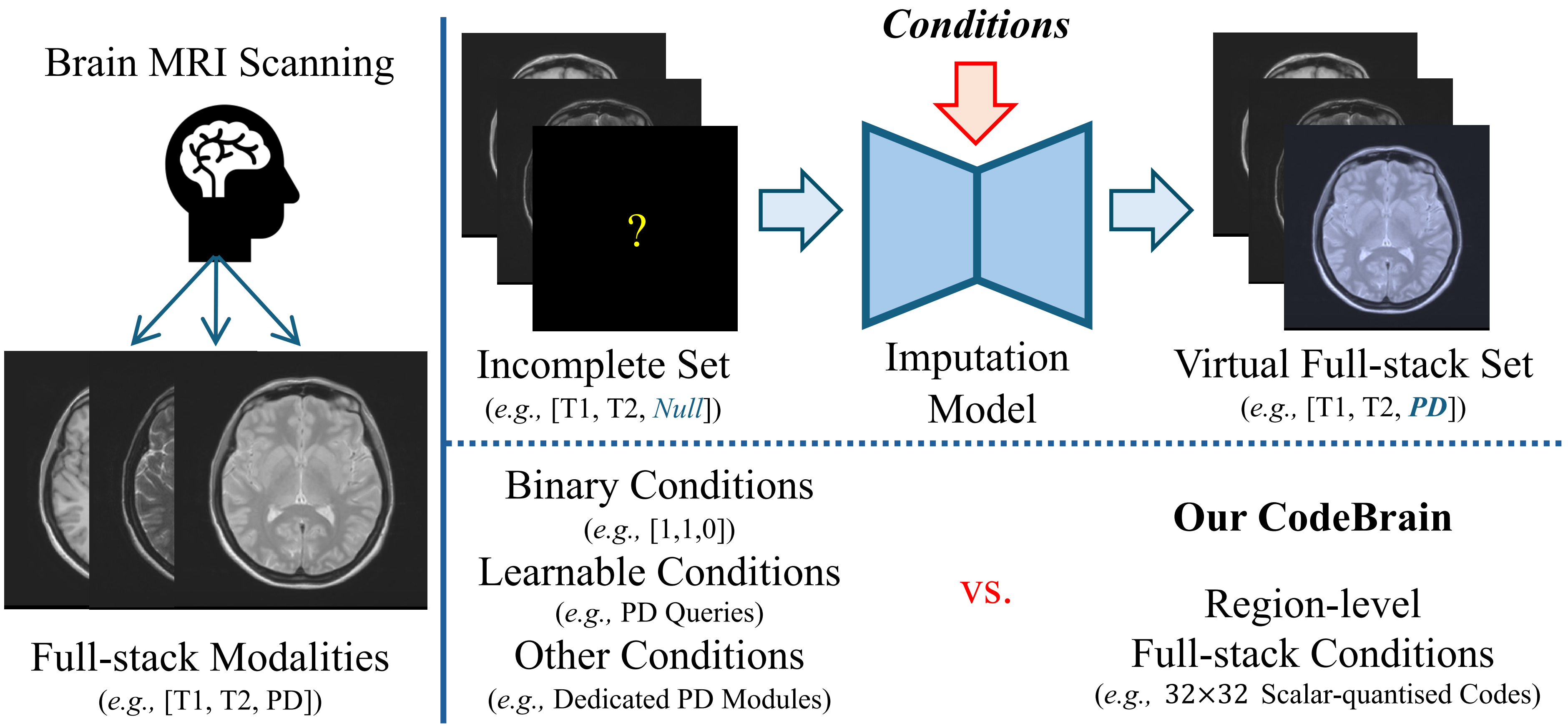
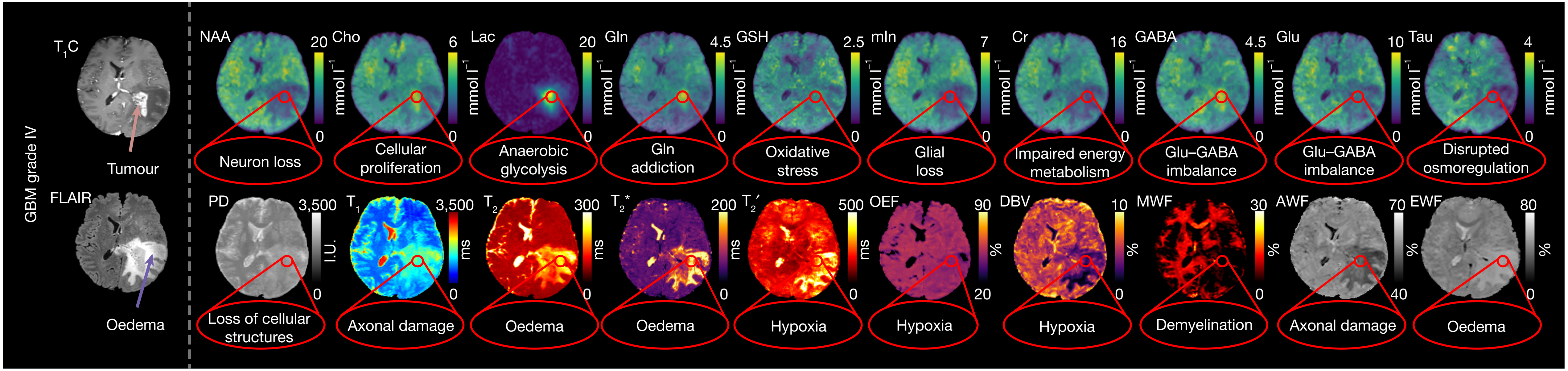


Background



MRI has revolutionized clinical examination;

Yet current practice still largely relies on separate acquisition protocols, each providing only one qualitative biomarker at a time;
Some protocols, such as contrast-agent-enhanced imaging, are quite costly and may introduce potential health risks.

Imputing missing modalities and achieving "**Virtual Full-stack Scanning**" of brain MRI is highly desirable.

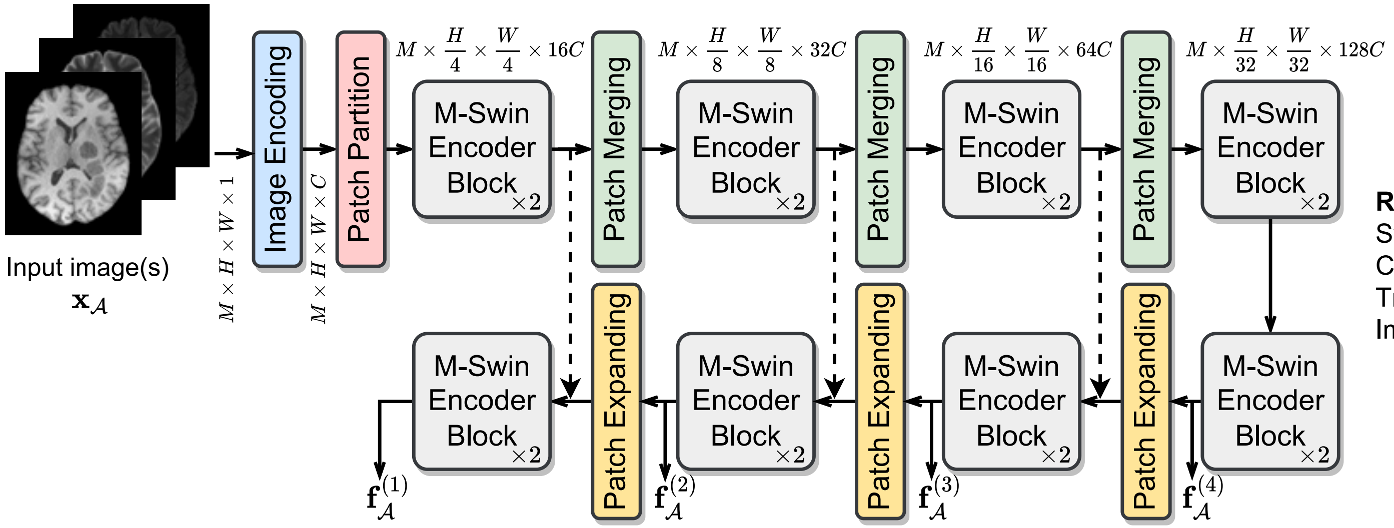
Ref: Li et al. "Multiplexed magnetic resonance imaging". NATURE, 2026

Related Work

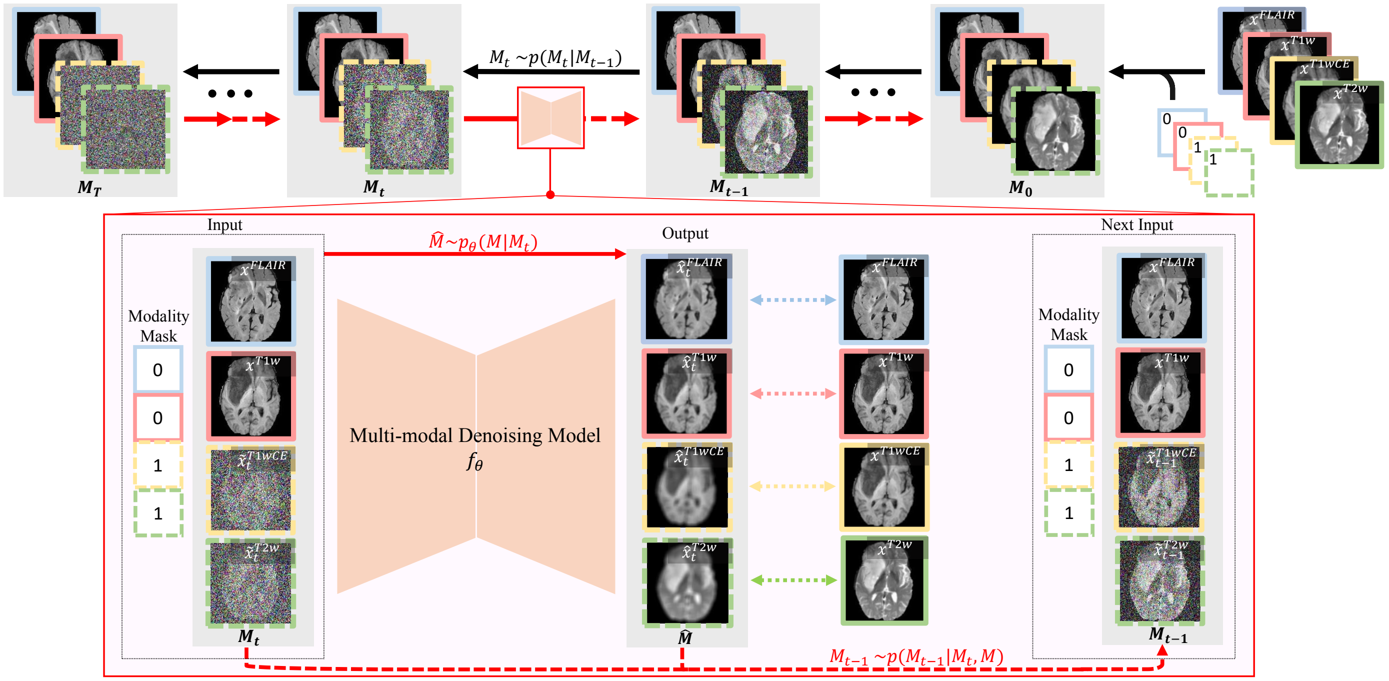
Powerful AI Tools

[1] Transformer-based Model;

[2] Diffusion-based Model;



Ref: Liu et al. "One Model to Synthesize Them All: Multi-Contrast Multi-Scale Transformer for Missing Data Imputation". TMI, 2023



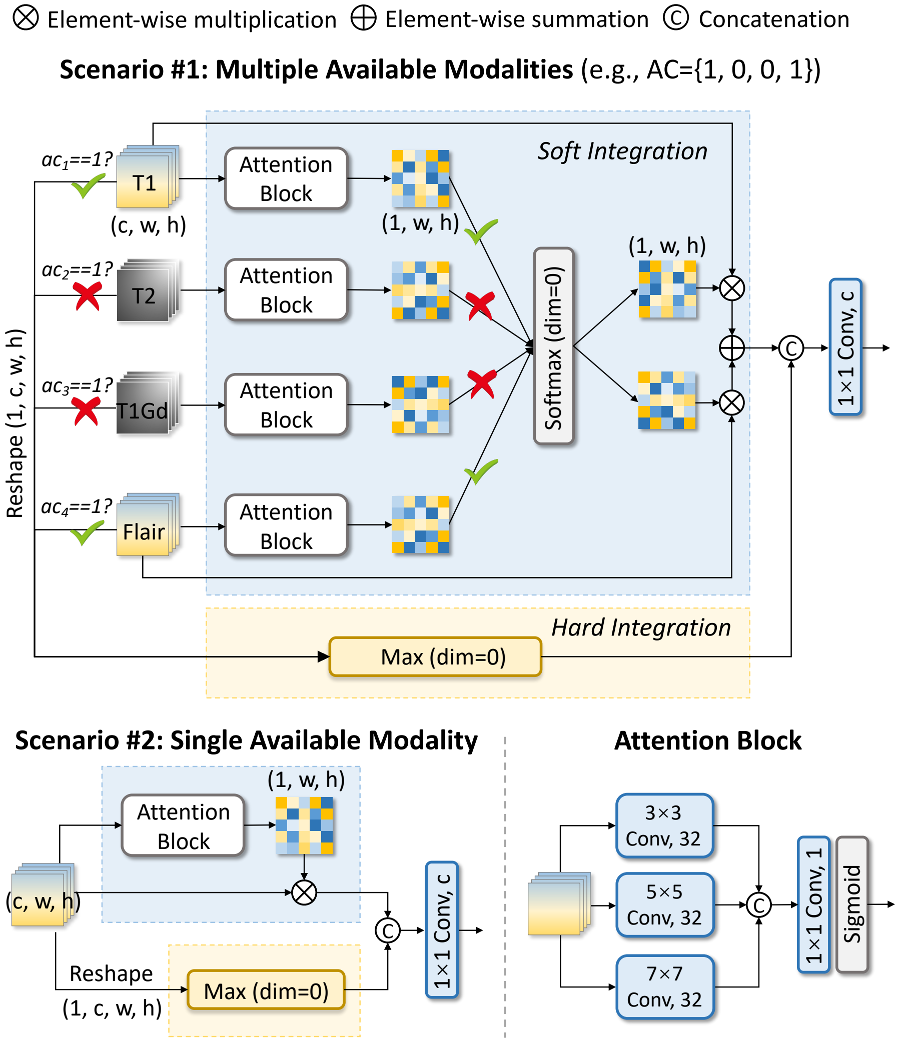
Ref: Meng et al. "Multi-modal Modality-masked Diffusion Network for Brain MRI Synthesis with Random Modality Missing". TMI, 2024

Related Work

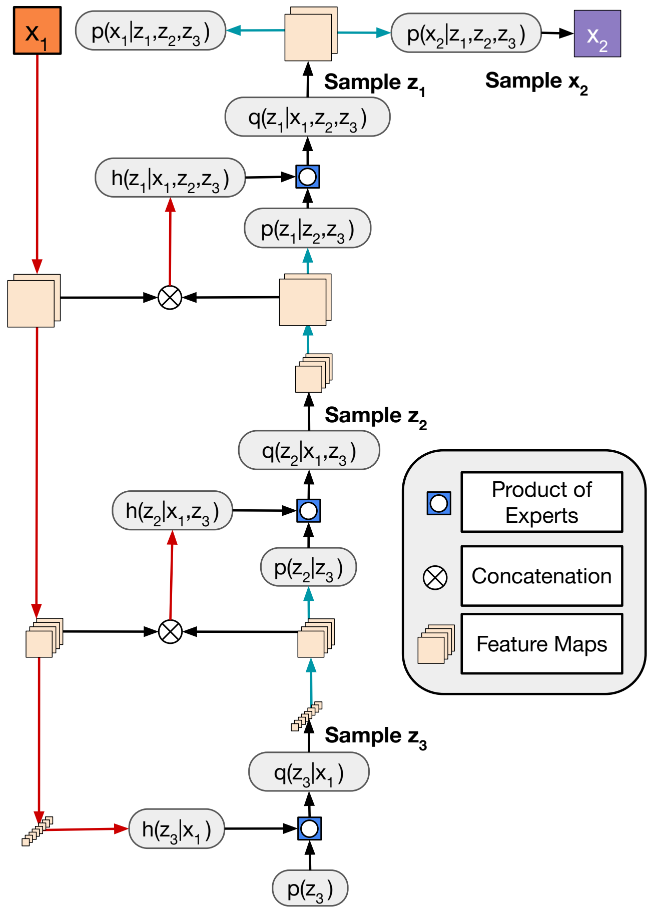
Divide-and-Conquer

[1] Single vs Multiple Inputs;

[2] Hierarchical Latent Fusion



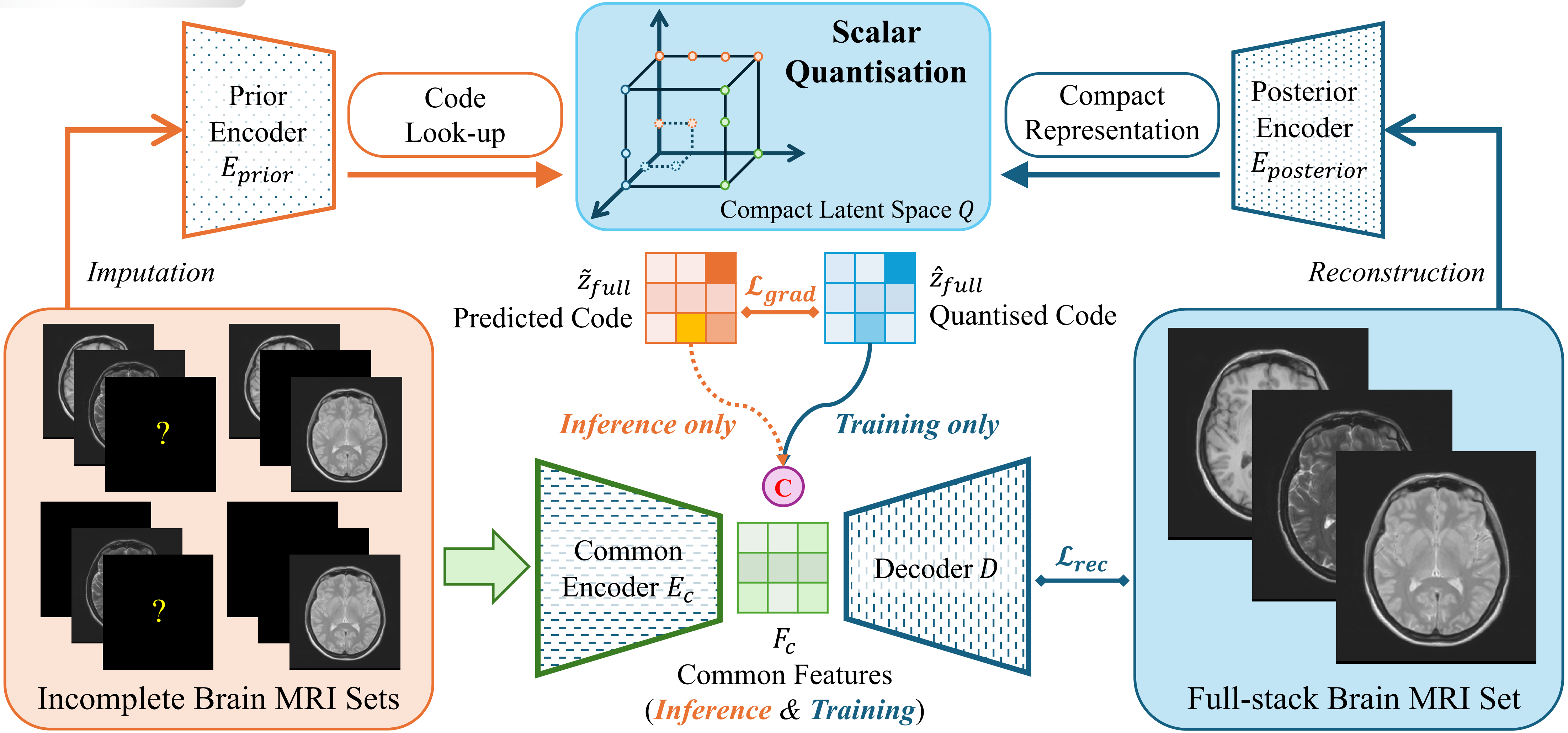
Ref: Zhang et al. "Unified Multi-Modal Image Synthesis for Missing Modality Imputation". TMI, 2024



Ref: Dorent et al. " Unified Cross-Modal Medical Image Synthesis with Hierarchical Mixture of Product-of-Experts". TPAMI, 2025

Method

Bottleneck Feature Representation



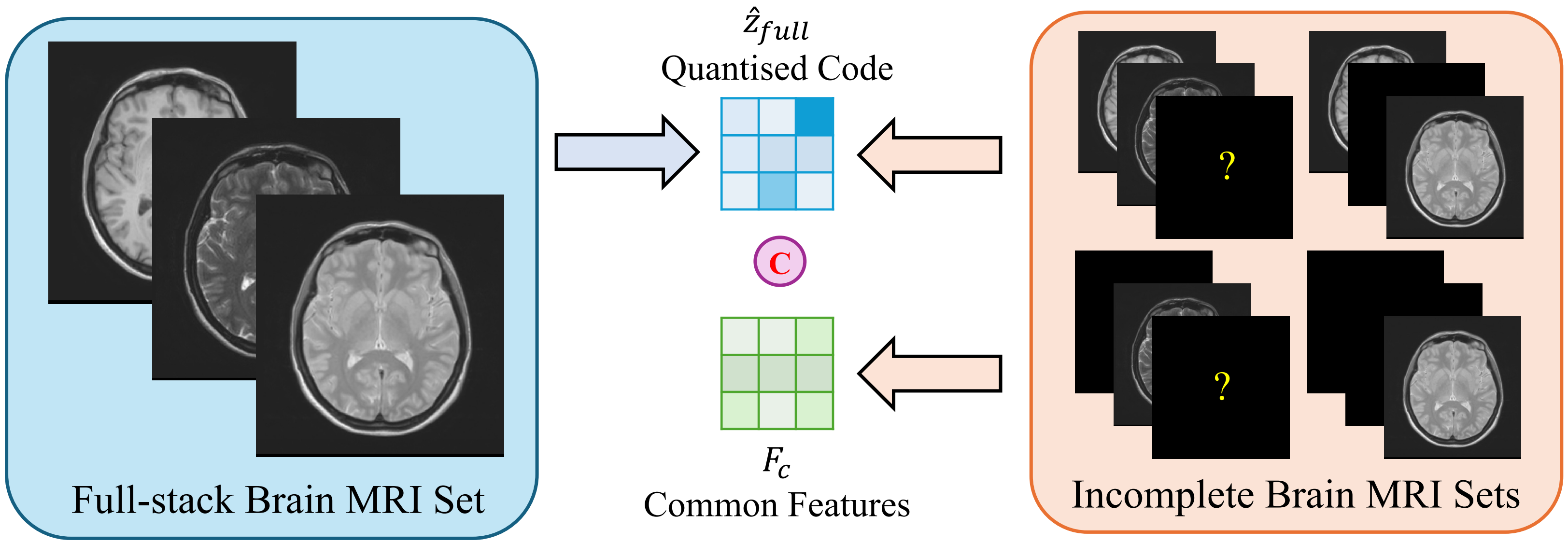
Method

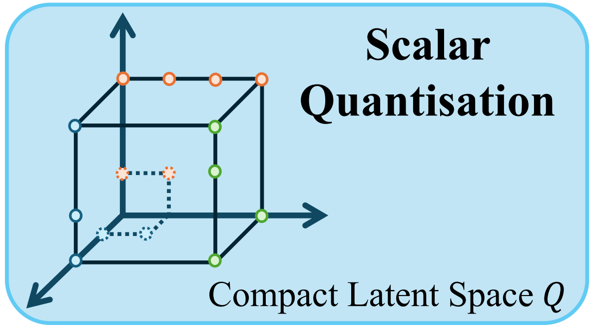
CodeBrain enables the
Unified Imputation

by predicting quantised FSQ codes representing the complete MRI set,

from incomplete inputs.

[1] **Common Features**
[2] **Grading** (Ordinal Regression)





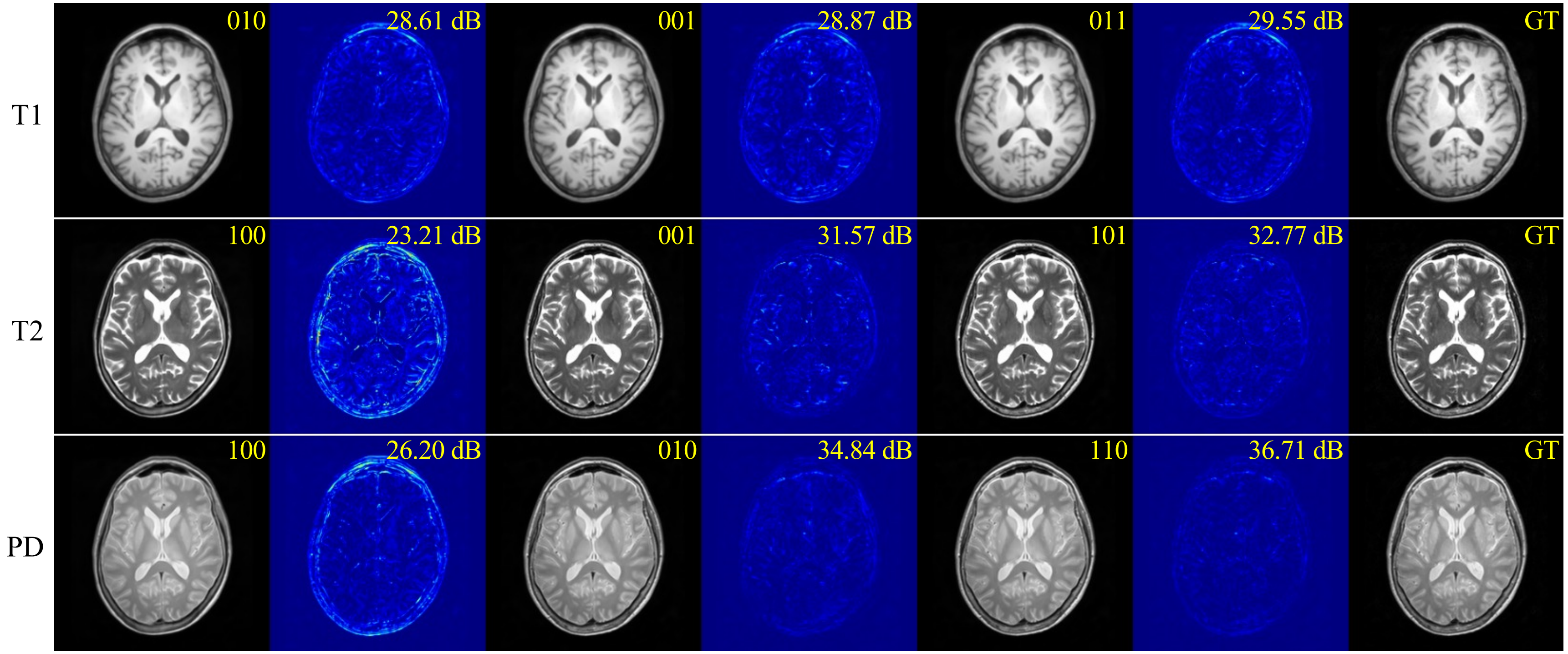
Cls labels	Grad labels
0	000
1	100
2	110
3	111

Ref: Fabian et al. " Finite Scalar Quantization: VQ-VAE Made Simple". ICLR, 2023

Result

Scenarios			T1 (Missing)			T2 (Missing)			PD (Missing)		
T1	T2	PD	PSNR (dB) ↑	SSIM (%) ↑	MAE (×1000) ↓	PSNR (dB) ↑	SSIM (%) ↑	MAE (×1000) ↓	PSNR (dB) ↑	SSIM (%) ↑	MAE (×1000) ↓
		√	28.51 (35.45)	93.51 (97.36)	17.95 (8.52)	30.08 (33.09)	93.76 (95.12)	15.92 (12.00)		N/A	
	√		28.08 (35.09)	93.20 (97.15)	19.04 (8.92)		N/A		33.42 (36.87)	96.12 (97.29)	11.59 (8.00)
√				N/A		23.61 (27.82)	86.20 (91.23)	30.54 (19.93)	27.10 (31.83)	89.97 (94.32)	21.26 (12.84)
√	√			N/A			N/A		34.65 (38.17)	96.48 (97.65)	10.15 (7.02)
√		√		N/A		31.08 (34.16)	94.16 (95.48)	14.76 (10.97)		N/A	
	√	√	28.95 (36.36)	94.01 (97.85)	16.93 (7.64)		N/A			N/A	
mean			28.51 (35.64)	93.57 (97.45)	17.97 (8.36)	28.26 (31.69)	91.37 (93.94)	20.41 (14.30)	31.72 (35.63)	94.19 (96.42)	14.33 (9.29)

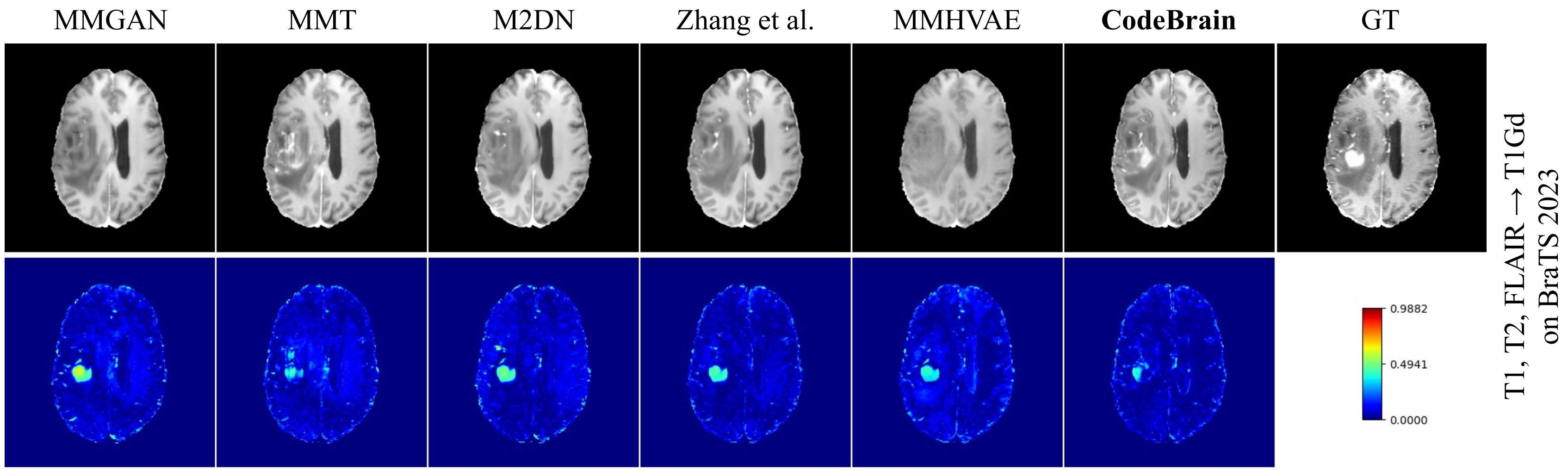
Across diverse scenarios, **CodeBrain** achieves superior reconstruction and imputation performance in brain MRI.



Result

Methods \ Metrics	PSNR (dB) ↑			SSIM (%) ↑			MAE (×1000) ↓		
	mean	O→O	M→O	*mean*	O→O	M→O	*mean*	O→O	M→O
MMGAN [34]	27.64	26.76	29.41	90.84	89.71	93.10	21.39	23.31	17.55
MMT [26]	28.06	27.11	29.96	91.42	90.30	93.65	20.21	22.19	16.25
M2DN [27]	28.14	27.38	29.67	91.80	90.95	93.49	19.69	21.22	16.64
Zhang et al. [49]	29.00	28.08	30.85	92.63	91.63	94.62	18.40	20.10	15.00
MMHVAE [10]	28.11	27.23	29.88	91.20	90.15	93.29	20.14	21.96	16.51
Our CodeBrain	**29.50**	**28.47**	**31.56**	**93.05**	**92.13**	**94.88**	**17.57**	**19.38**	**13.95**
MMGAN [34]	24.28	23.76	24.68	89.11	88.22	89.78	23.72	25.15	22.65
MMT [26]	24.58	23.88	25.11	89.47	88.38	90.30	22.65	24.55	21.22
M2DN [27]	24.34	23.69	24.83	89.65	88.72	90.35	22.95	24.70	21.64
Zhang et al. [49]	25.01	24.31	25.54	89.98	89.00	90.72	21.53	23.31	20.20
MMHVAE [10]	24.29	23.66	24.76	88.83	87.88	89.54	23.63	25.46	22.25
Our CodeBrain	**25.31**	**24.67**	**25.79**	**90.49**	**89.64**	**91.12**	**21.01**	**22.57**	**19.84**

Compared to other SOTA models, **CodeBrain** outperforms them in three image quality metrics & syntheses correct enhanced regions.



Ablation

Two **Key** components:

[1] Common features complement the quantised information loss;

[2] The grading loss captures the code clustering characteristics;

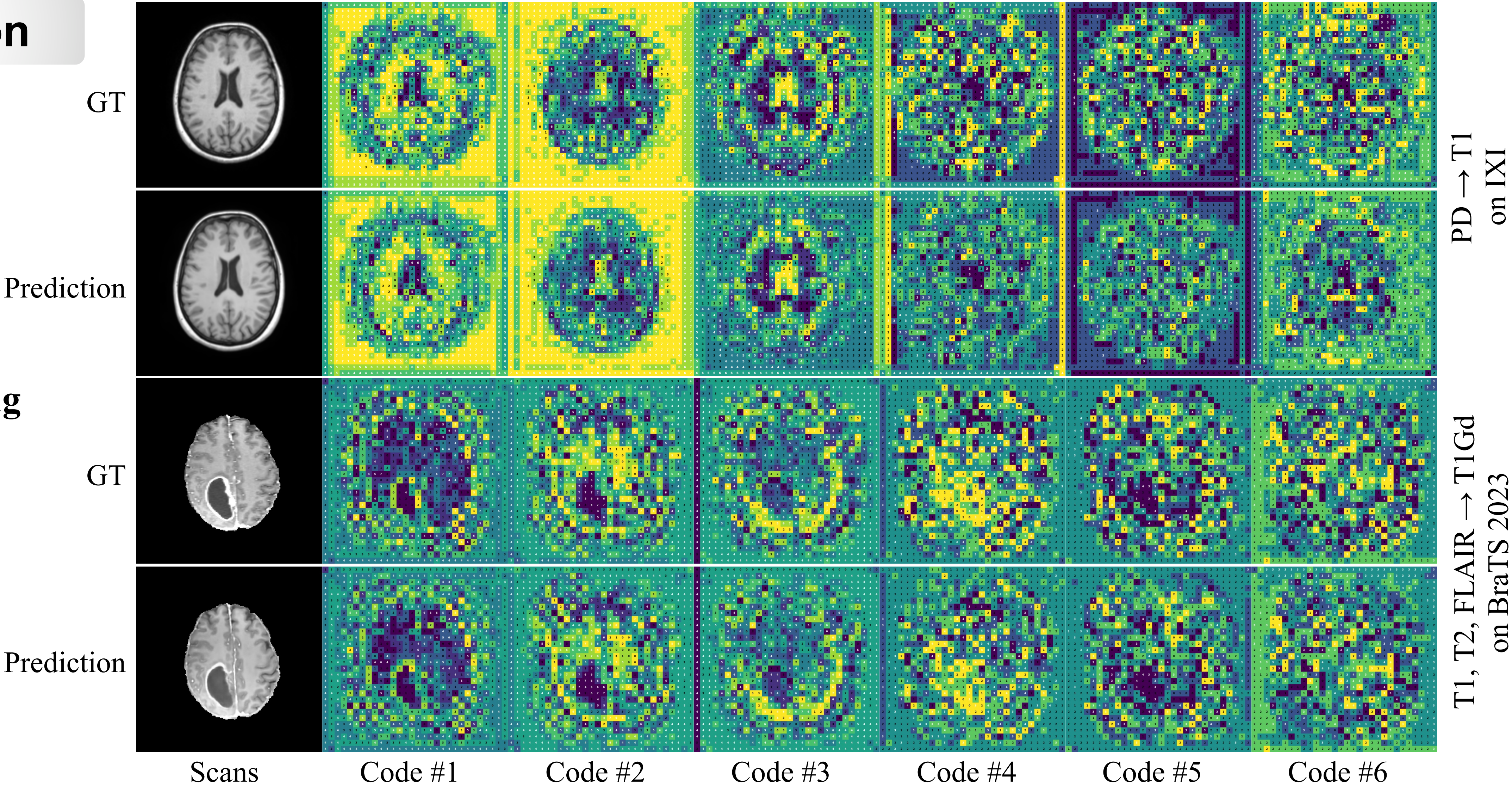
Stages	Settings	PSNR (dB) ↑	SSIM (%) ↑	MAE (×1000) ↓
Rec.	w/o F_c	30.15	92.75	15.87
	w/ F_c	**34.32**	**95.94**	**10.65**
Imp.	w/ Cls.	29.24	92.83	18.00
	w/ Grad.	**29.50**	**93.05**	**17.57**

λ_m	λ_a	PSNR (dB) ↑
10	5	33.83
20		**34.32**
30		34.21

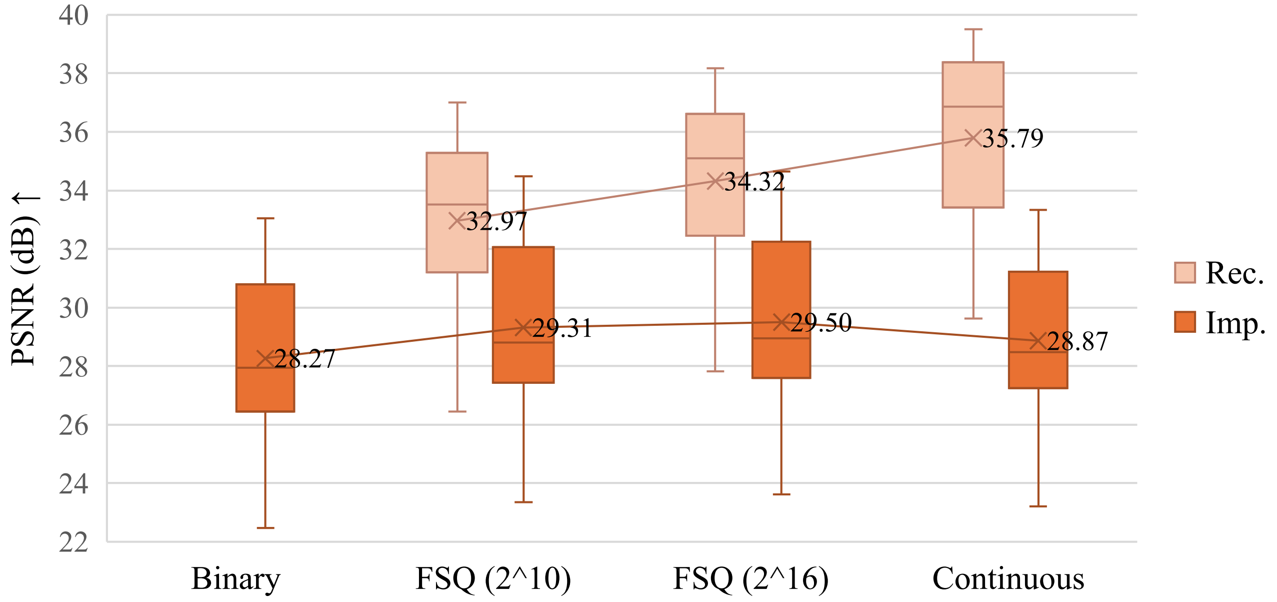
λ_m	λ_a	PSNR (dB) ↑
20	3	34.26
	5	**34.32**
	7	34.01

Discussion

Code Clustering



Discussion



Codebook size is a trade-off;

Downstream tumor segmentation:

[1] Missing FLAIR → failed segmentation;
[2] CodeBrain outperforms others;
[3] CodeBrain approaches the upper bound

	T1	T2	FLAIR	T1Gd	*mean*
Zero Imputation	47.58	77.39	0.84	27.75	38.39
MMT [26]	86.07	**87.08**	85.90	57.25	79.08
Zhang et al. [49]	**86.26**	85.90	86.31	47.35	76.46
MMHVAE [10]	85.90	85.02	**86.73**	40.22	74.47
Our CodeBrain	86.10	86.23	86.47	**61.44**	**80.06**
Full Modalities	87.40				

Conclusion

A Unified Model for Imputing Any Missing Modality

Given one potential incomplete MRI set, the proposed **CodeBrain** model can impute any missing modality and achieve a virtual full-stack scanning in brain MRI.

Technical Design

CodeBrain operates in two stages: it first encodes each complete brain MRI set into quantised codes, and then learns to predict these codes from incomplete inputs.

Take-home Message

The complete brain MRI modality set can be represented as region-level quantised codes, so that diverse "Any-to-Any" imputation tasks can be transformed from pixel-level synthesis into a unified latent code prediction.