



# FluenceFormer: Transformer-Driven Multi-Beam Fluence Map Regression for Radiotherapy Planning

Ujunwa Mgboh<sup>1</sup>, Rafi Ibn Sultan<sup>1</sup>, Joshua Kim<sup>2</sup>, Kundan Thind<sup>2</sup> and Dongxiao Zhu<sup>1</sup>,

<sup>1</sup> Wayne State University, Michigan, United States, <sup>2</sup> Henry Ford Health, Michigan, United States



## INTRODUCTION

### MOTIVATION:

- Fluence map prediction is central to automated radiotherapy planning
- Ill-posed inverse problem: complex mapping to beam intensities
- Leads to: Structurally inconsistent plans and physically unrealizable fluence maps

**OBJECTIVE(S):** 1) To develop a geometry-aware deep learning framework for fluence prediction

2) To improve structural fidelity and energy consistency

3) To ensure generalizability across multiple transformer backbones

## METHODOLOGY

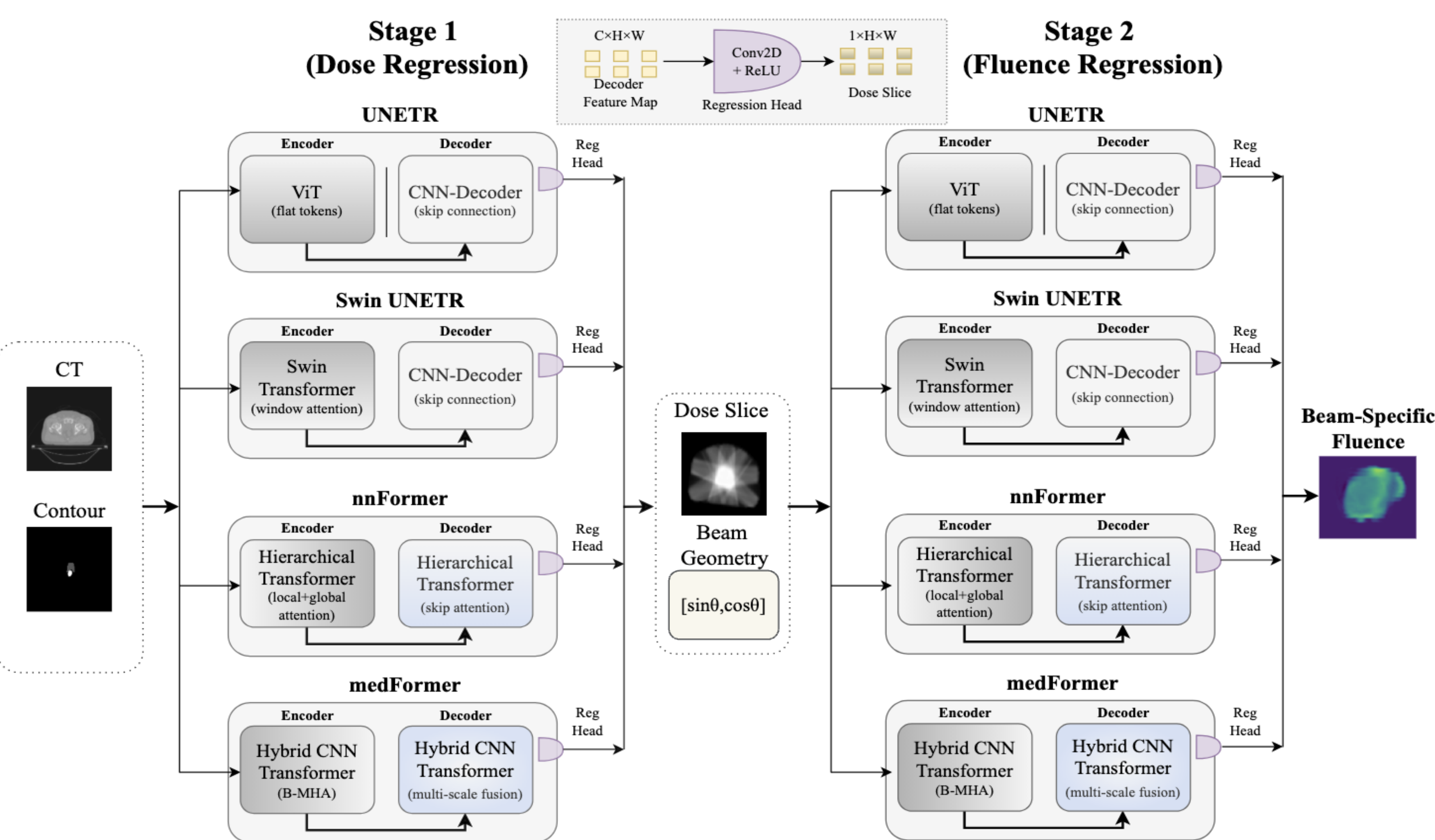
### METHOD OVERVIEW:

- Geometry-aware transformer framework
- Two-stage formulation (**Figure 1**):
- Stage1: Predict global dose from anatomy
- Stage2: Conditioned on beam geometry to predict fluence

### KEY COMPONENTS:

- Backbone-agnostic: Swin UNETR, UNETR, nnFormer, MedFormer
- Geometry encoding
- Intermediate dose
- FAR Loss (Physics-Informed)

$$\mathcal{L}_{\text{FAR}} = \alpha \mathcal{L}_{\text{MSE}} + \beta \mathcal{L}_{\text{Grad}} + \gamma \mathcal{L}_{\text{Corr}} + \delta \mathcal{L}_{\text{Energy}}, \quad \alpha, \beta, \gamma, \delta \geq 0.$$



**Figure 1: Overview of the FluenceFormer framework. Stage 1 performs slice-wise dose regression from anatomical inputs. Stage 2 conditions the predicted dose on explicit geometric encoding.**

## RESULTS

**Table 1: Comprehensive comparison against naive baselines, strong literature baselines, and the proposed FluenceFormer framework.**

Category	Method/Backbone	MAE ↓	Energy Err (%) ↓	PSNR ↑	SSIM ↑
Naive Baselines (Seg-Style)	UNETR (Hatamizadeh et al., 2022)	0.20 ± 0.06	22.1 ± 8.4	13.62 ± 1.28	0.43 ± 0.06
	Swin UNETR (Hatamizadeh et al., 2021)	0.11 ± 0.01	20.4 ± 9.7	15.53 ± 1.48	0.50 ± 0.05
	nnFormer (Zhou et al., 2021)	0.21 ± 0.01	22.1 ± 9.3	13.58 ± 1.50	0.45 ± 0.07
	MedFormer (Gao et al., 2022)	0.14 ± 0.02	20.3 ± 8.4	14.79 ± 1.47	0.40 ± 0.03
	Strong Baselines (Direct Reg.)	Standard CNN (U-Net) (Wang et al., 2020)	0.05 ± 0.06	8.4 ± 8.9	16.00 ± 1.57
	Single-Stage Swin UNETR (Mgboh et al., 2025)	0.05 ± 0.07	7.1 ± 8.9	16.45 ± 1.46	0.67 ± 0.08
FluenceFormer (Two-Stage)	UNETR	0.06 ± 0.02	7.0 ± 9.6	16.19 ± 1.54	0.60 ± 0.08
	Swin UNETR	<b>0.02 ± 0.06*</b>	<b>6.1 ± 8.9*</b>	<b>17.99 ± 1.59*</b>	<b>0.70 ± 0.07*</b>

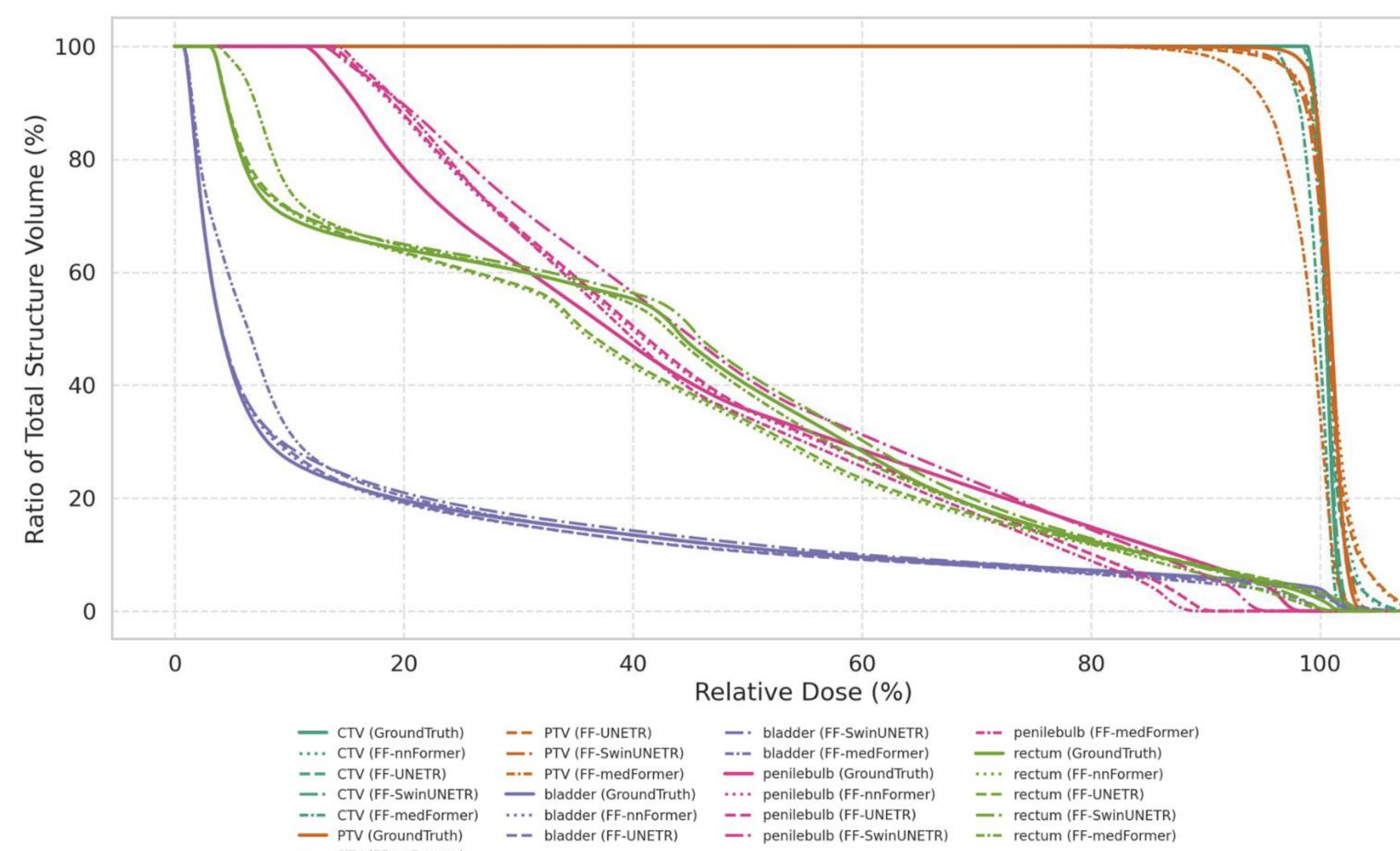
\*Indicates statistically significant improvement over Strong Baselines ( $p < 0.05$ ).

## RESULTS

**Table 2: Backbone-Agnostic Validation of the FluenceFormer Framework.**

Backbone	Loss Function	MAE ↓	Energy Err (%) ↓	PSNR ↑	SSIM ↑
Swin UNETR	Baseline (MSE)	0.02 ± 0.06	6.10 ± 8.90	17.99 ± 1.59	0.70 ± 0.07
	MSE + Energy	0.03 ± 0.01	7.44 ± 3.46	17.12 ± 1.52	0.67 ± 0.07
	MSE + Grad	0.04 ± 0.04	6.82 ± 2.07	16.98 ± 1.49	0.67 ± 0.08
	<b>Proposed FAR</b>	<b>0.02 ± 0.01</b>	<b>4.53 ± 2.54*</b>	<b>18.14 ± 1.57</b>	<b>0.76 ± 0.08*</b>
UNETR	Baseline (MSE)	0.06 ± 0.02	7.01 ± 9.60	16.19 ± 1.54	0.60 ± 0.08
	MSE + Energy	0.05 ± 0.01	6.78 ± 3.92	17.19 ± 1.36	0.67 ± 0.07
	MSE + Grad	0.05 ± 0.02	7.08 ± 2.75	17.34 ± 1.30	0.52 ± 0.08
	<b>Proposed FAR</b>	<b>0.04 ± 0.01</b>	<b>6.74 ± 2.15*</b>	<b>17.21 ± 1.42</b>	<b>0.67 ± 0.07*</b>
nnFormer	Baseline (MSE)	0.03 ± 0.01	10.44 ± 9.73	17.73 ± 1.41	0.53 ± 0.06
	MSE + Energy	0.02 ± 0.07	11.87 ± 3.28	17.84 ± 1.46	0.56 ± 0.06
	MSE + Grad	0.03 ± 0.01	10.34 ± 1.62	17.80 ± 1.45	0.54 ± 0.07
	<b>Proposed FAR</b>	<b>0.02 ± 0.00</b>	<b>9.10 ± 2.90*</b>	<b>18.01 ± 1.45</b>	<b>0.58 ± 0.06*</b>
MedFormer	Baseline (MSE)	0.03 ± 0.01	8.79 ± 7.16	17.10 ± 1.51	0.60 ± 0.06
	MSE + Energy	0.03 ± 0.02	12.66 ± 2.60	17.71 ± 1.47	0.59 ± 0.06
	MSE + Grad	0.03 ± 0.01	10.72 ± 2.04	17.65 ± 1.45	0.59 ± 0.06
	<b>Proposed FAR</b>	<b>0.02 ± 0.07</b>	<b>7.50 ± 2.20*</b>	<b>17.85 ± 1.50</b>	<b>0.65 ± 0.06*</b>

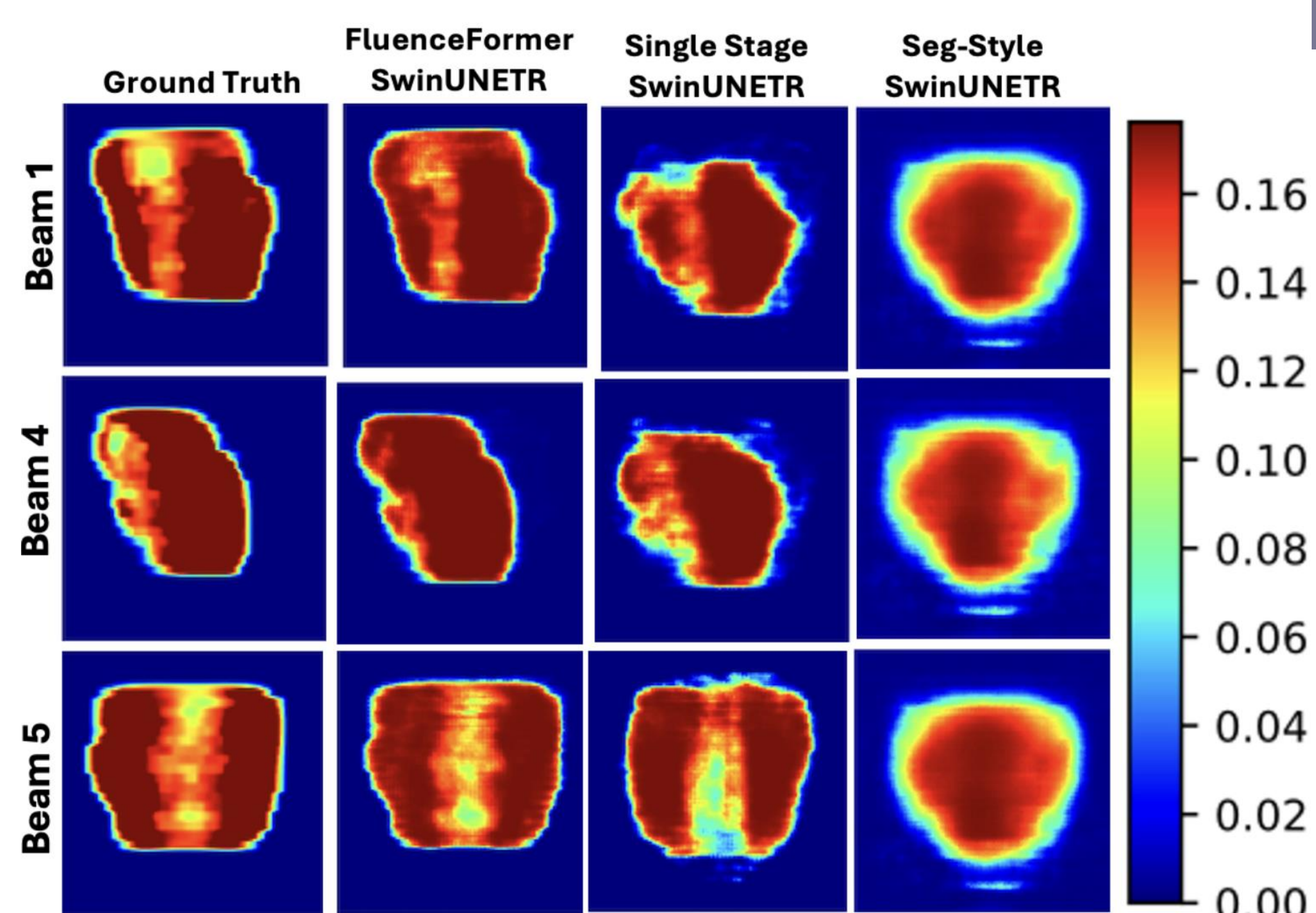
\*Indicates statistically significant improvement over Baseline ( $p < 0.05$ ).



**Figure 3: DVH comparison using TPS-recalculated dose from predicted fluences.**

**Table 3: Oracle-conditioned Stage 2 performance and slice-wise stability.**

Model	MAE ↓	PSNR ↑	SSIM ↑	Z-Consistency ↓
Swin UNETR	0.015 ± 0.005	20.5 ± 2.1	0.82 ± 0.03	<b>0.10</b>
UNETR	0.021 ± 0.008	19.8 ± 2.5	0.78 ± 0.05	0.26
nnFormer	0.019 ± 0.006	18.5 ± 2.3	0.60 ± 0.04	0.33
MedFormer	0.018 ± 0.006	18.8 ± 2.2	0.71 ± 0.04	0.25

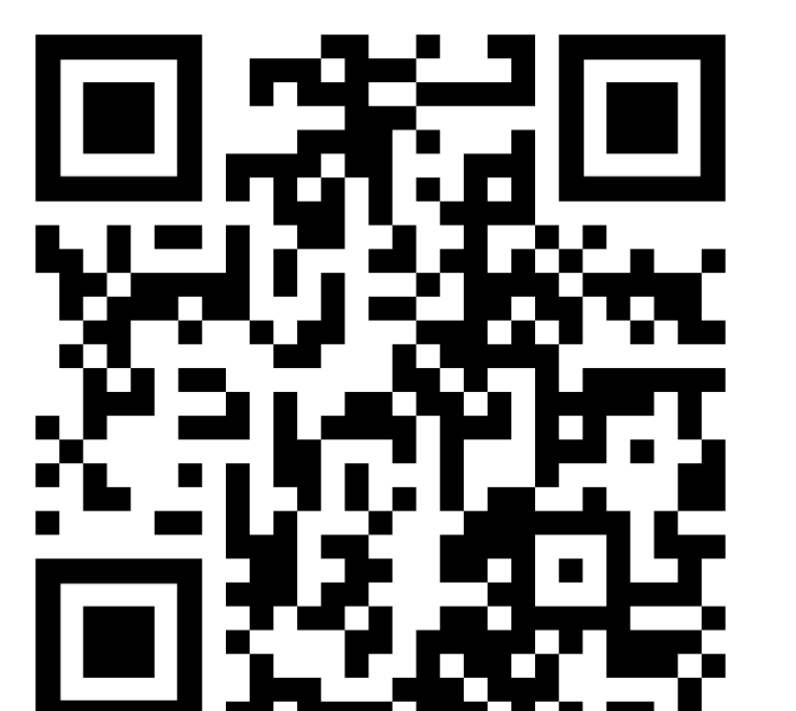


**Figure 2: Qualitative comparison of fluence predictions. Methods correspond to Table 1**

## RESOURCES & CODE



GitHub Repository



Paper Link