GEPAR3D: Geometry Prior-Assisted Learning for 3D Tooth Segmentation

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Introduction

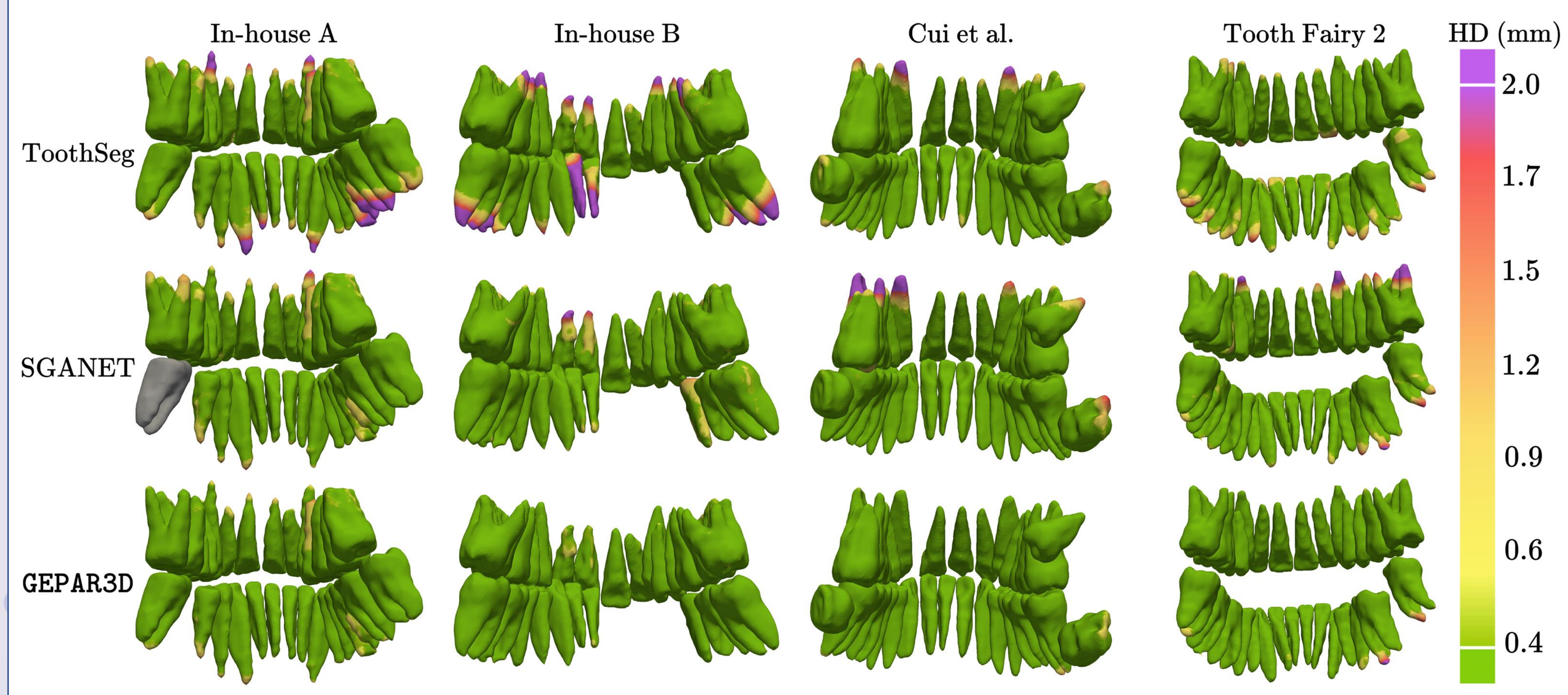
Problem: Accurate 3D tooth segmentation in CBCT is essential for orthodontic planning and root resorption detection. Small root apices and their morphological variability make segmentation challenging.

Limitations of Existing Methods: Current approaches neglect full anatomical structure and inter-class relationships, rely on fragmented pipelines or limited geometric priors, resulting in incomplete delineation of root apices.

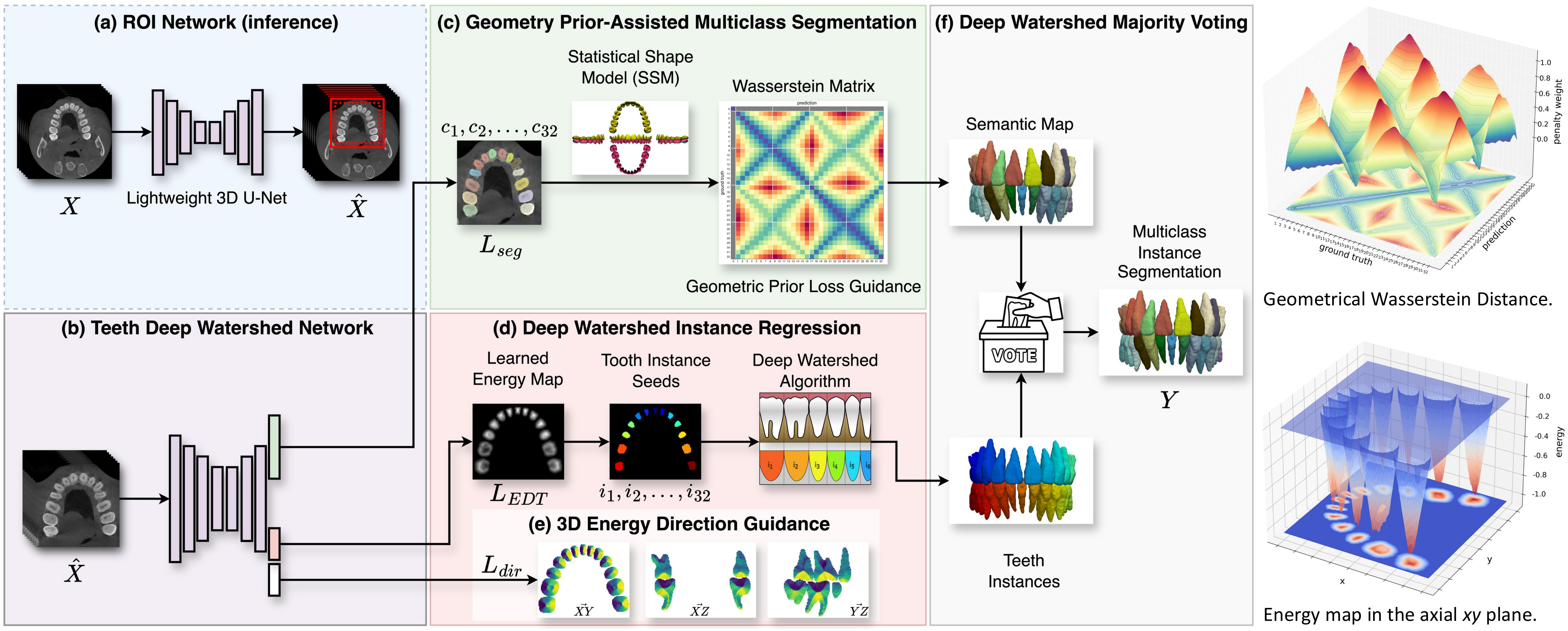
GEPAR3D:

- Unifies instance detection and multi-class segmentation in a single step,
- Integrates a **Statistical Shape Model** to embed anatomical context and ensure morphological consistency,
- Models each tooth as a 3D energy basin, encoding voxel distances and directional gradients to capture subtle variations at root apices.

Existing methods struggle with root apices segmentation

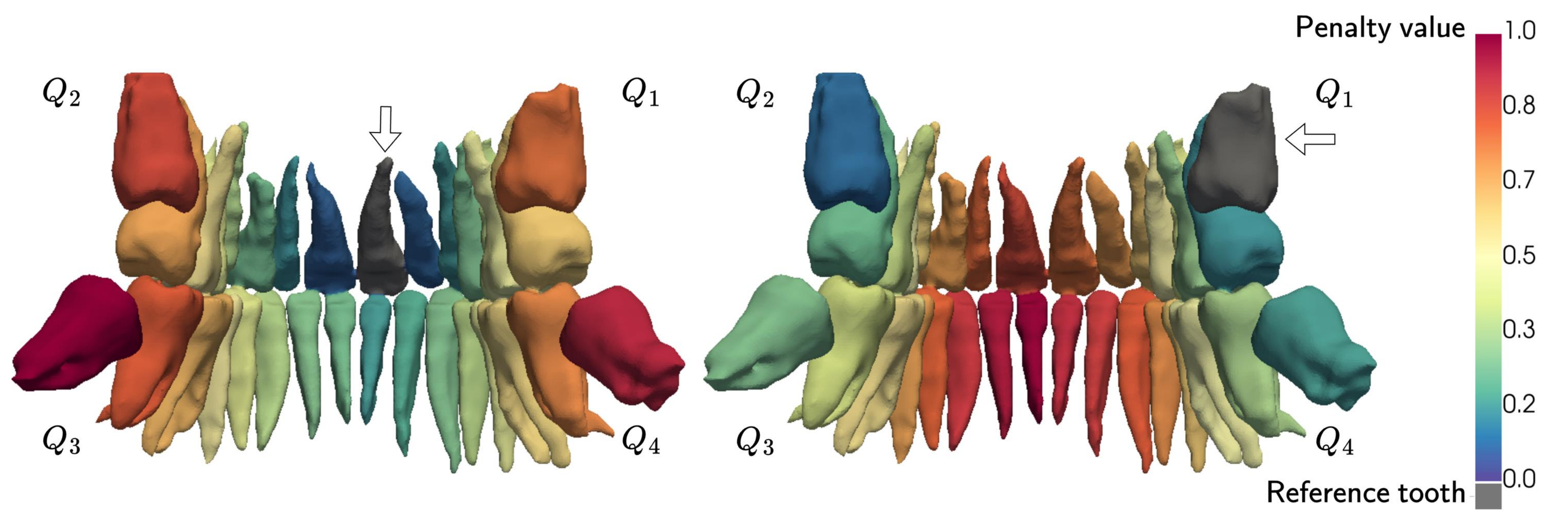


Qualitative comparison of **GEPAR3D** with top baselines. Surface Hausdorff Distance heatmaps show apex deviations; our approach improves root sensitivity.

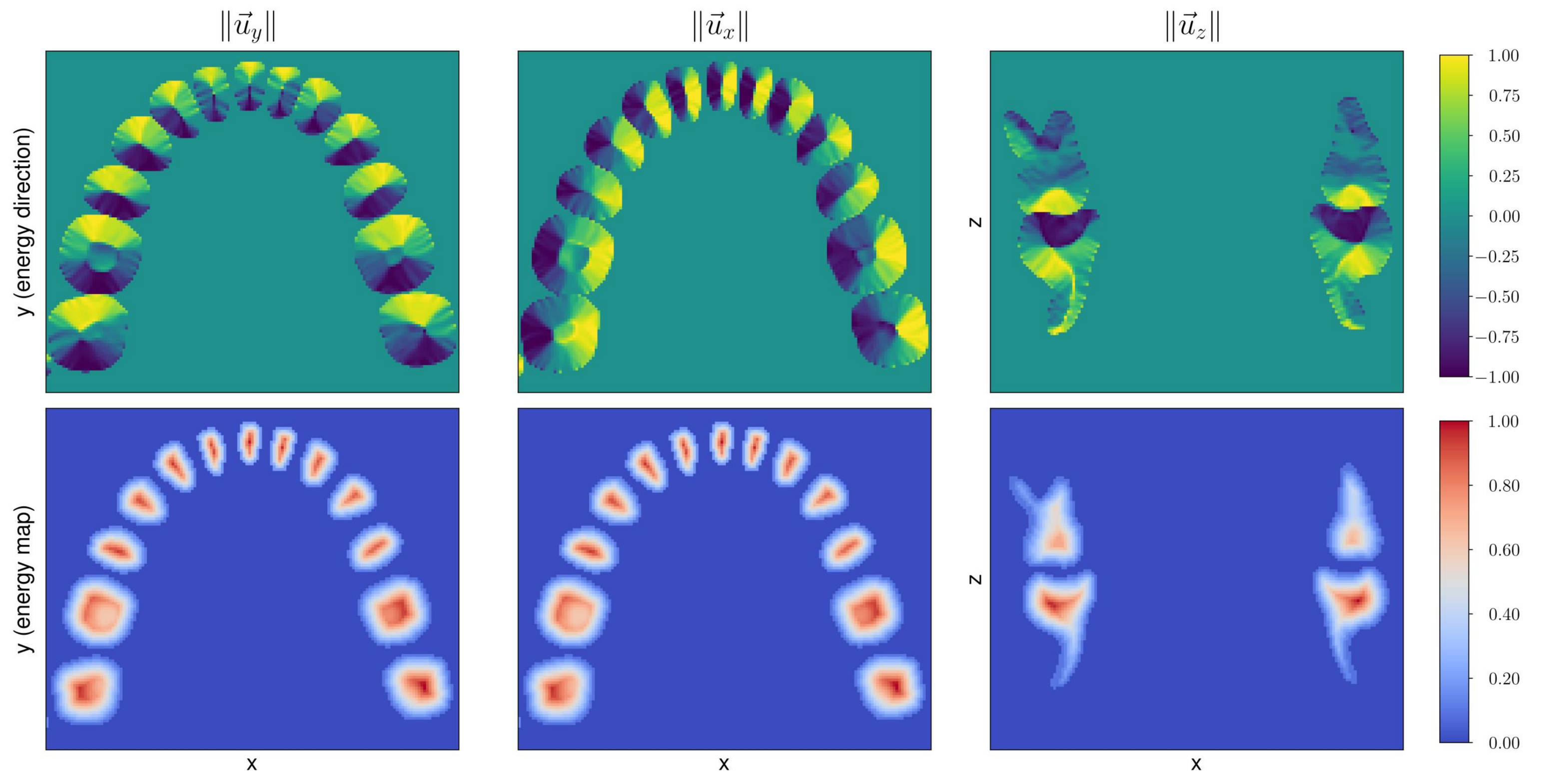


An overview of **GEPAR3D**, which unifies instance detection and multi-class segmentation for precise tooth root segmentation. (a) Crops the region of interest (ROI) during inference. (b) Simultaneously performs multi-class segmentation and instance regression. (c) Regularizes segmentation loss L_{seg} with a geometric prior from an SSM of normal dentition. (d) Uses instance regression task L_{EDT} to generate energy maps for the 3D Deep Watershed Algorithm. (e) Captures complex root apex geometries via Energy Direction loss L_{dir}. Finally, (f) assigns each detected instance a class via majority voting based on segmentation outputs.

Geometrical and morphological inductive bias



Intermediate step of the Wasserstein loss calculation: 3D heatmaps show class penalties relative to reference teeth. Highest penalties occur for morphologically and spatially distant teeth.



Energy direction and distance map reveal sharp vector transitions around root apices, highlighting regions needing fine-grained guidance to prevent tooth instance fusion or under-segmenting root apices.

Quantitative comparison of **GEPAR3D** and SOTA methods. Metrics: DA/F1 = instance detection, DSC/RC/HD = multi-class, NSD_1/RCB = binary. Results averaged over three datasets; best and second-best highlighted. I = instance, S = semantic, IS = instance-based multi-class, TF2 = Tooth Fairy 2. † indicates p < 0.05.

Method	Type	DA (%)↑	F1 (%)↑	DSC (%)↑ In-house	DSC (%)↑ Cui et al.	DSC (%)↑ TF2	DSC (%)↑ Average	RC (%)↑	HD (mm)↓	NSD_1 (%)↑	RC_B (%)↑
U-Net †	S	95.6(4.6)	93.5(6.3)	87.8(3.4)	88.7(3.3)	88.3(3.1)	88.2(3.8)	85.5(5.0)	21.78(11.24)	88.2(5.1)	90.6(2.9)
Swin SMT †	S	98.1(3.1)	96.8(4.0)	92.8(2.5)	92.9(2.5)	91.4(3.0)	92.3(2.8)	91.1(4.2)	2.93(1.89)	94.6(3.3)	92.9(3.2)
Swin UNETR †|	S	97.9(3.3)	96.6(4.6)	92.8(2.7)	92.6(2.3)	92.3(2.4)	92.6(2.7)	91.3(3.8)	3.41(2.57)	94.5(3.4)	93.3(2.7)
Swin UNETRv2 †	S	98.1(3.3)	97.3(4.0)	92.7(3.2)	93.2(2.5)	93.4(1.8)	93.1(2.7)	91.6(4.3)	2.42(1.19)	95.5(3.4)	93.1(3.2)
ResUNet34 †|	S	98.4(3.5)	97.5(4.5)	93.5(2.1)	93.4(2.3)	93.0(2.7)	93.3(2.4)	90.6(3.9)	2.19(1.56)	96.0(2.9)	91.8(3.2)
VSmTrans †	S	98.9(2.3)	97.7(3.6)	93.2(2.8)	93.5(1.7)	93.8(1.7)	93.5(2.3)	92.1(3.7)	9.06(7.91)	95.5(3.3)	94.1(2.5)
V-Net †|	S	98.9(2.5)	97.8(3.5)	93.7(1.7)	93.8(2.1)	93.2(2.3)	93.5(2.1)	92.4(3.6)	1.96(0.70)	95.9(2.9)	94.0(2.8)
Jang et al.†|	I	96.0(6.2)	-	83.5(1.6)	82.6(2.0)	82.5(1.3)	83.0(1.8)	75.6(6.1)	3.07(0.76)	79.3(3.0)	76.6(5.1)
MWTNet †|	I	92.6(8.4)	-	87.4(1.4)	84.3(2.0)	89.3(1.1)	87.4(2.5)	73.9(9.2)	2.29(0.59)	85.7(4.3)	76.3(6.2)
TSG-GCN †	S	86.9(9.7)	83.0(11.4)	89.3(1.7)	91.0(3.4)	87.8(1.9)	89.2(3.0)	76.8(11.2)	2.47(0.76)	90.1(4.5)	86.3(4.9)
ToothSeg †|	IS	88.8(10.5)	86.2(7.5)	89.3(1.8)	93.6(0.8)	89.8(1.7)	90.4(2.6)	80.2(11.1)	2.84(1.67)	91.3(5.1)	81.0(8.0)
SGANet †|	S	92.9(9.6)	90.8(10.4)	92.2(1.6)	92.9(2.5)	91.9(1.8)	92.2(2.1)	83.8(9.4)	2.18(0.74)	94.3(3.2)	85.7(5.9)
GEPAR3D	IS	**99.2(2.4)**	**98.0(3.7)**	**95.5(1.2)**	**95.1(0.8)**	**94.3(1.1)**	**95.0(1.4)**	**93.9(3.2)**	**1.44(0.70)**	**97.6(1.9)**	**95.2(2.1)**

Ablation study of network and loss components. Metrics: DA = detection accuracy, PR = precision, RC = recall, NSD = normalized surface dice. G = Geometric Prior, E = Energy map, D = Direction map, U0,1 = uniform cost. † indicates p < 0.05.

#	G	E	D	DSC (%)↑	PR (%)↑	RC (%)↑	NSD_1 (%)↑	DA(%) ↑	F1 (%)↑
1†	-	-	-	93.27(2.40)	94.59(3.73)	90.62(3.85)	95.95(2.94)	98.4(3.5)	97.5(4.5)
2†	($U_{0,1}$)	-	-	93.49(2.35)	90.78(5.31)	92.76(3.53)	95.96(2.83)	99.2(2.0)	98.2(3.3)
3†	✓	-	-	94.55(1.49)	91.67(5.39)	92.86(2.35)	96.05(1.94)	**99.3(1.9)**	**98.4(3.2)**
4†	-	✓	-	94.58(1.28)	**95.55(2.94)**	91.36(3.67)	97.25(1.93)	99.2(2.2)	98.0(3.5)
5†	-	✓	✓	94.68(1.13)	95.52(2.86)	91.65(3.81)	97.41(1.83)	99.2(2.4)	98.0(3.5)
6†	✓	✓	-	94.96(1.13)	94.33(3.24)	93.12(3.33)	97.58(1.90)	99.1(2.5)	97.9(3.6)
7	✓	✓	✓	**95.01(1.36)**	94.95(3.45)	**93.90(3.18)**	**97.63(1.94)**	99.2(2.4)	98.0(3.7)

Conclusions: **GEPAR3D** improves tooth segmentation, especially at root apices, outperforming SOTA methods on public datasets. Geometric priors combined with instance regression enhance precision while mitigating sensitivity issues. Future work will include larger datasets, self-supervised learning, and sequential CBCTs.

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PROJECT

CODE