DeepOPG: Improving Orthopantomogram Finding Summarization with Weak Supervision

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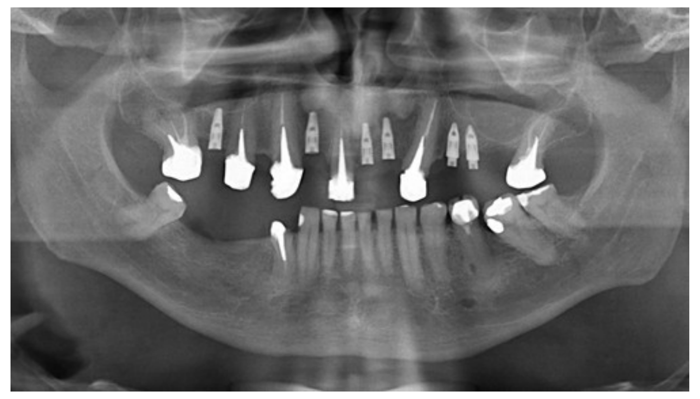
Full Paper

Motivation & Contributions

- An *orthopantomogram (OPG)* is a half-circle 2D scanning of the oral region
- Interpretation of OPGs suffers from *low* inter-rater agreement among clinicians
- Current models to derive OPG finding summary all require *time-consuming per-pixel* annotations

Orthopantomogram



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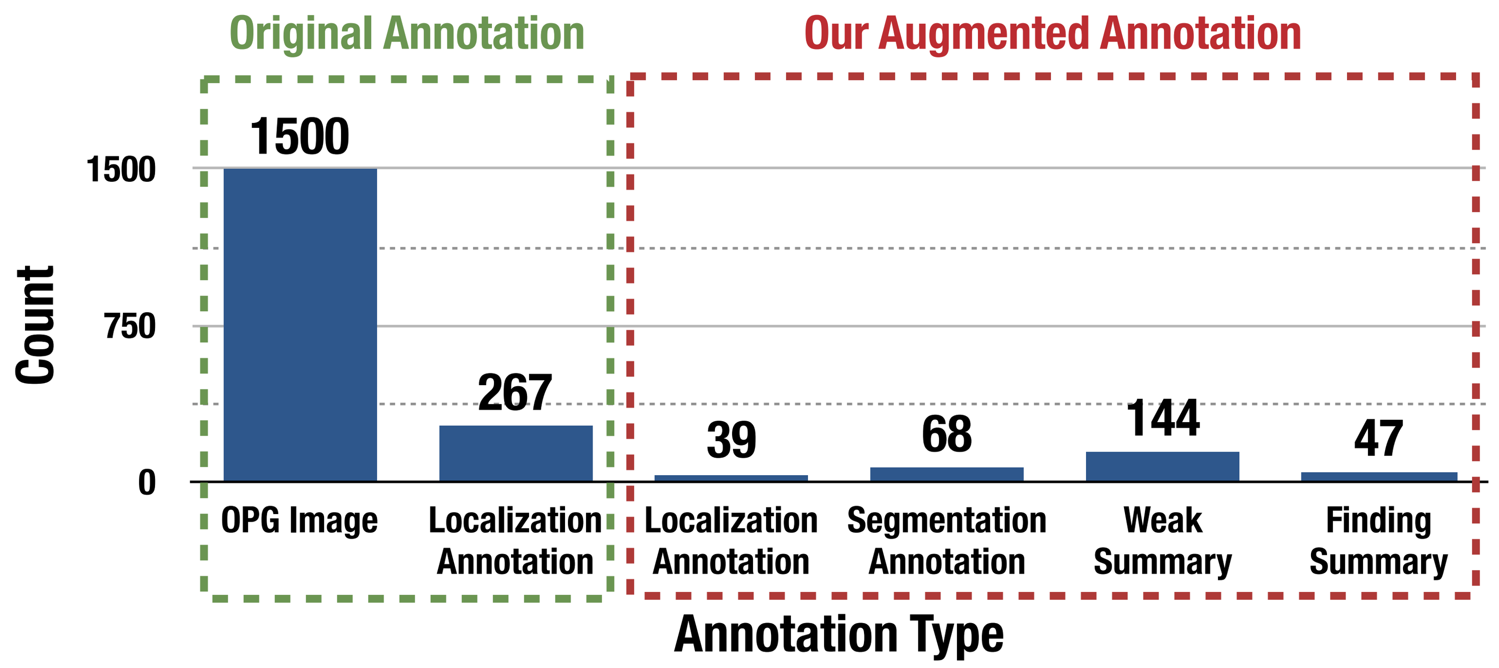
Finding Summary

Type	Subtotal	FDI #
Missing Teeth	14	...
Impacted Teeth	0	...
Teeth with Crown & Bridge	11	...
Teeth with Restorations	2	...
Root Filled Teeth	7	...
Implants	6	...

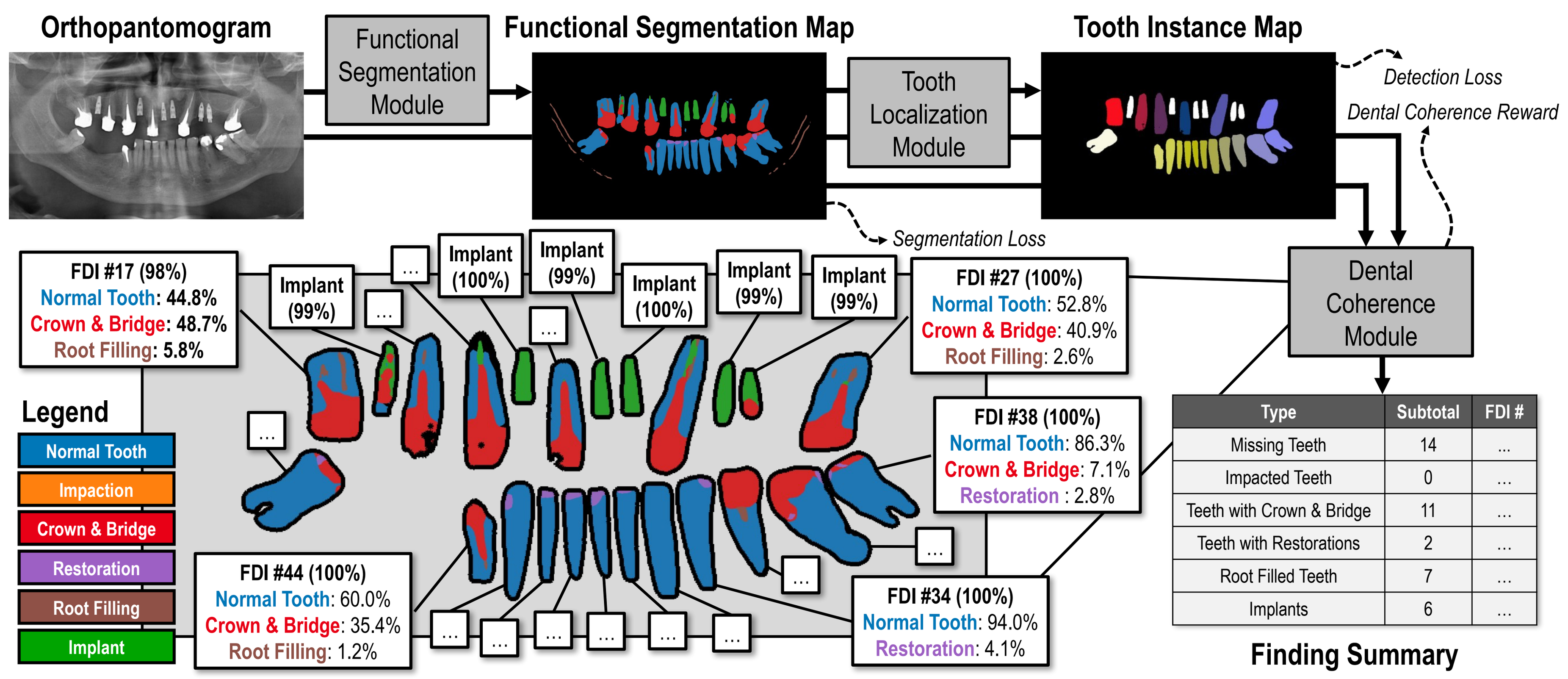
- We propose DeepOPG, a system to predict OPG finding summary with
  (1) weak supervision data, and
  (2) dental knowledge infused

Data: UFBA-UESC Dental Images



Methods: Dental Coherence Reward

Overview



- ***Functional Segmentation Module*** (ResNet-50 + U-Net) first takes OPG and derives the *7-class functional segmentation map:* **background**, **normal (non-impacted) teeth**, **impaction**, **crown & bridge**, **restoration**, **root filling material**, and **implant**
- ***Tooth Localization Module*** (ResNet-101 + RPN) then takes OPG and <u>segmentation map</u> and derives the *34-class instance map:* background, 32 teeth in FDI notation, and implant
- ***<u>Dental Coherence Module</u>*** refines the instance ↔ teeth assignment $\mathbf{E}$ by maximizing the clinical knowledge-based *Dental Coherence Reward*
  - ***Inference-Time Decoding:*** solve a Generalized Quadratic Assignment Problem (GQAP) with no model modifications
  - ***<u>Weakly Supervised Reinforcement Learning (RL)</u>:*** use weak summary data and REINFORCE to learn better models

probability distributions over classes for instances

instance ↔ teeth assignment

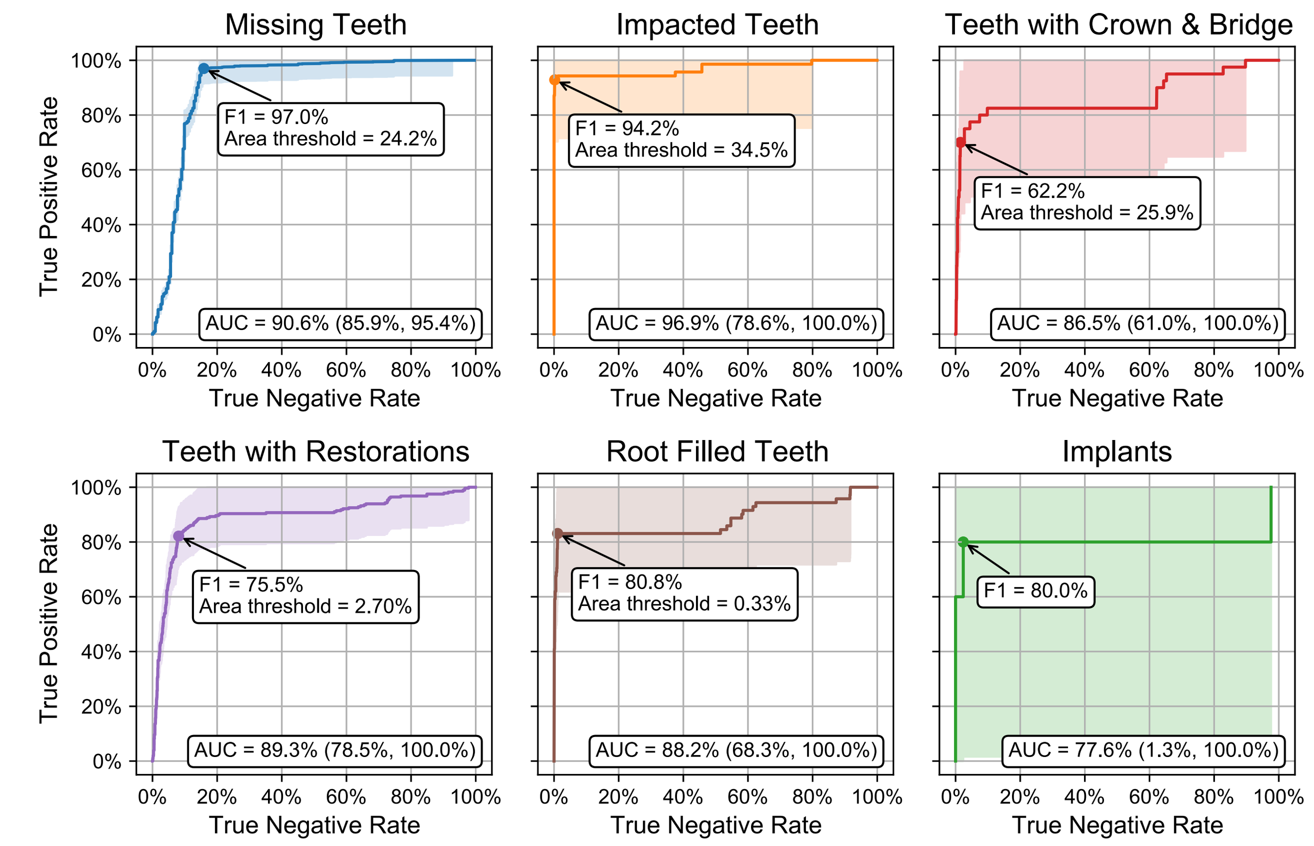
$$r_{\mathrm{DCR}}\left(\mathbf{P},\mathbf{E},\mathbf{M}\right) \equiv \sum_{n,c} p_{nc}\cdot e_{nc} - \sum_{n,c,m,d} q_{ncmd}\cdot e_{nc}\cdot e_{md}$$

instance masks — *IoU between instance masks*

- We **(A)** train Functional Segmentation first, then **(B)** train Tooth Localization w/o RL, followed by **(C)** fine-tuning with RL.

Results

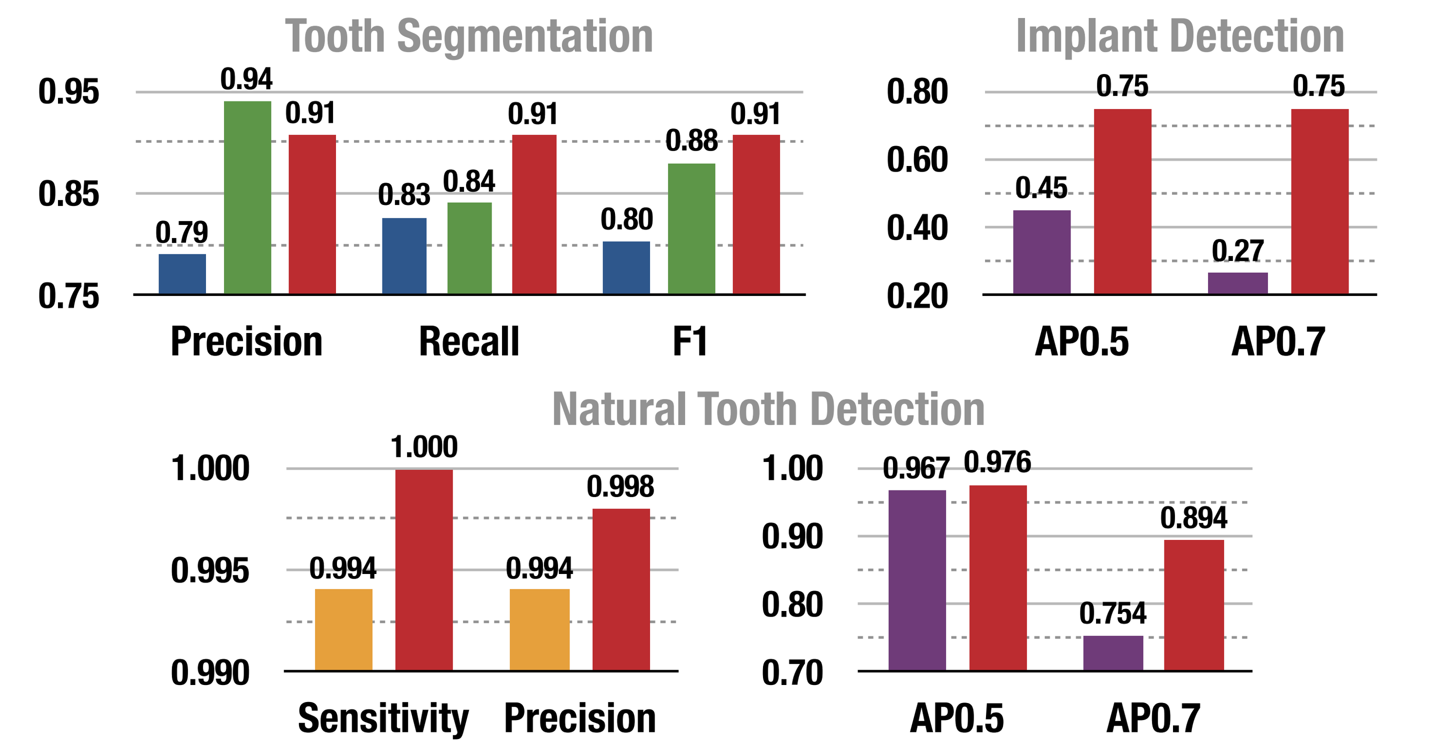
Receiver Operating Characteristic of Findings



Tooth Localization Performance: Ablation Study

Method	Per-Object				Per-Image
	$AP_{0.0}$ (%)	$AP_{0.5}$ (%)	DA (%)	FA (%)	IoU (%)
DeepOPG (full)	$\mathbf{98.6_{0.1}}$	$\mathbf{97.6_{0.3}}$	$\mathbf{98.7_{0.4}}$	$\mathbf{97.5_{0.6}}$	$\mathbf{80.5_{1.5}}$
w/o RL	$98.4_{0.1}$	$97.2_{0.4}$	$\mathbf{98.7_{0.4}}$	$\mathbf{97.5_{0.6}}$	$80.1_{1.5}$
w/o RL and dental coherence	$93.0_{0.1}$	$91.3_{0.4}$	$93.7_{0.9}$	$87.4_{1.2}$	$79.7_{1.6}$
w/o segmentation	$97.7_{0.1}$	$96.2_{0.3}$	$97.9_{0.5}$	$95.7_{0.8}$	$80.2_{1.5}$

Comparison to Prior Work



- **Wirtz et al.:** Automatic Teeth Segmentation in Panoramic X-ray Images Using a Coupled Shape Model in Combination with a Neural Network
- **Jader et al.:** Deep Instance Segmentation of Teeth in Panoramic X-ray Images
- **Tuzoff et al.:** Tooth Detection and Numbering in Panoramic Radiographs using Convolutional Neural Networks
- **Kim et al.:** Automatic Tooth Detection and Numbering Using a Combination of a CNN and Heuristic Algorithm
- **DeepOPG (full):** Ours with all features