Tooth Detection and Classification Using Dental X-ray Images

4th December, 2021

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Audience: Capstone Showcase

Agenda

Artificial Intelligence can be used to augment dental diagnosis

Dental X-ray images help screen for any tooth and bone structure abnormalities

- ➢ Solely relying on a dentist's opinion increases the likelihood of human error

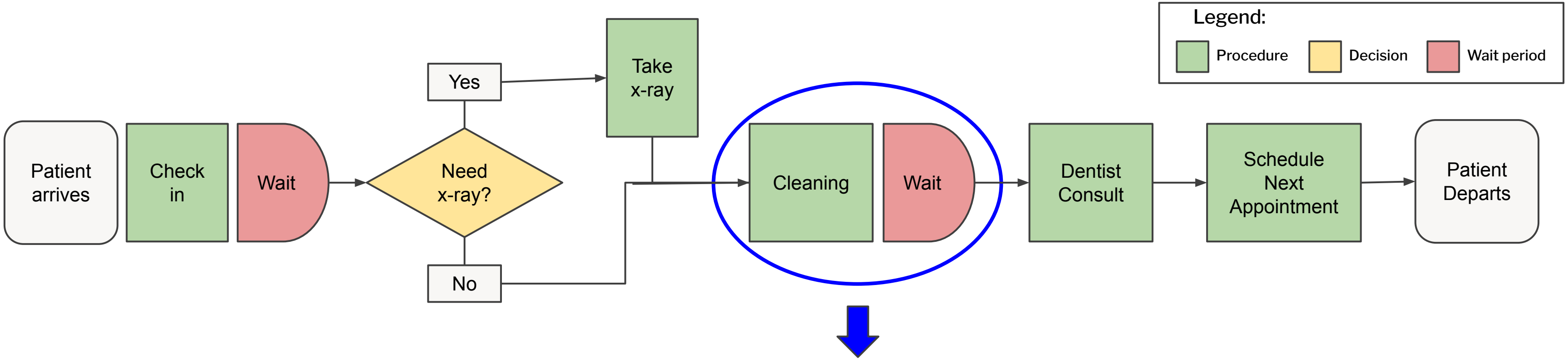
Great Lakes Dental Partners (GLDP) investing in dental AI products to assist dental diagnosis.

- ➢ Chicago's largest dental network

Images source: https://www.oregondentist.com/Blog/Post/The-Difference-in-Digital-Dental-X-Rays

Automation can increase patient throughput and dental clinic revenue

Typical Patient Process at Dental Visit



- ❖ Reduce patient wait time
- ❖ Increase diagnostic support
- ❖ Improve real time scheduling
- ❖ Increase ROI

Inference Analytics aims to enter the dental AI industry with a x-ray based tooth screening model

Key benefits of IANN's platforms:

- Enhance productivity
- Improvements in quality
- Reduced burnout

IANN
Inference Analytics Neural Network

Competitors in the dental AI industry:

- Overjet
- Denti.AI
- Pearl
- ORCA Dental AI

Images source: https://www.inferenceanalytics.com

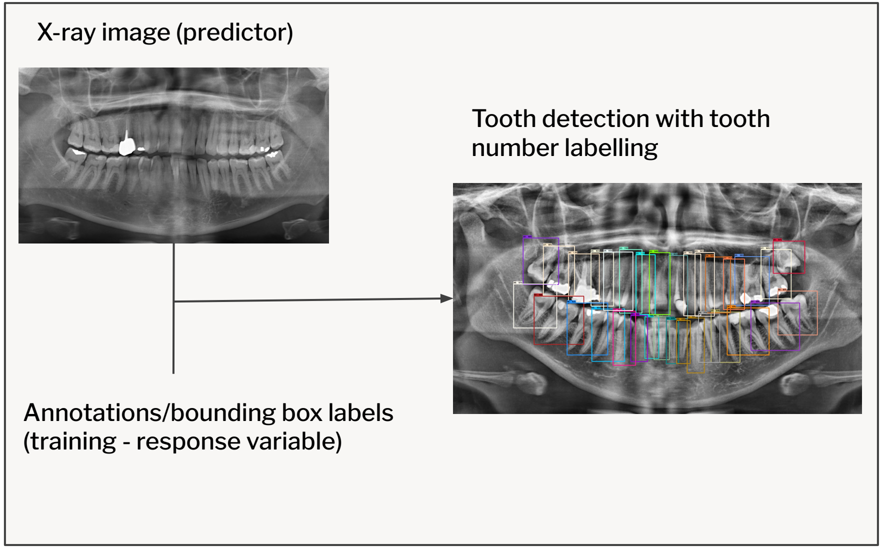
Deep learning approaches were utilized to automate tooth detection and labelling

Project Goals:

1. Automated tooth detection on panoramic dental X-ray images.
2. Tooth type classification with tooth number labelling

Outcome:

A deployable product with a graphical user interface for tooth detection and labelling.



Tooth detection and labelling of panoramic X-ray images

Images source: https://awesomeopensource.com/project/clemkoa/tooth-detection

Tooth segmentation is essential for furthering dental AI

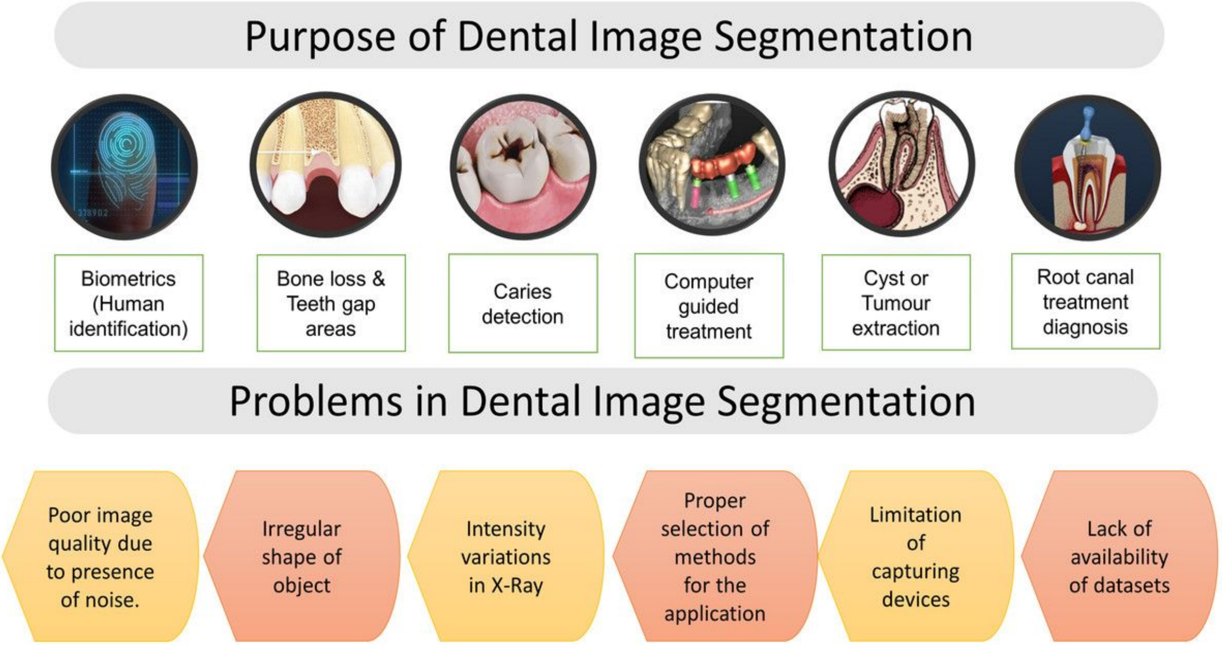
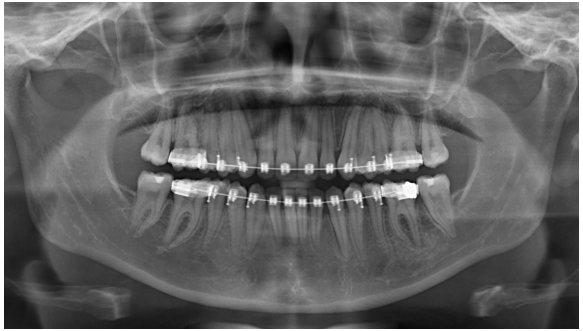


Image source: Kumar, A., Bhadauria, H. S., & Singh, A. (2021). Descriptive analysis of dental X-ray images using various practical methods: A review. *PeerJ Computer Science*, *7*, e620. https://doi.org/10.7717/PEERJ-CS.620

Panoramic dental x-rays from two different sources were utilized

X-ray from UFBA-UESC Dental Images

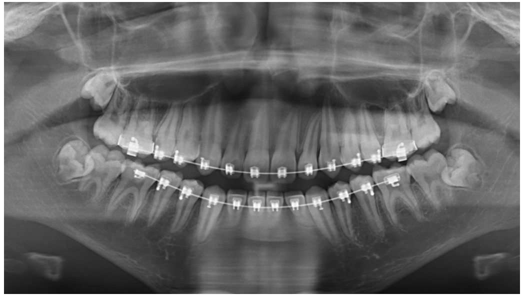


X-ray from Great Lakes Dental Practices

- UFBA-UESC Dental Images dataset contains 1500 panoramic dental x-ray images
  - Used in many dental research studies
- Collected 2 million panoramic dental x-ray images from around 40 clinics under GLDP specifically for IANN

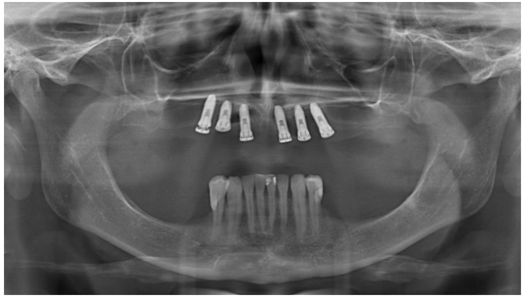
Variations in x-rays range from differences in each patient's mouth and teeth to x-ray quality

Dental appliance (e.g. braces)



Dental restoration (e.g. fillings)

Dental implant (e.g. fake teeth)



Jaw structure

X-ray quality (exposure)

X-ray quality (warping, text)

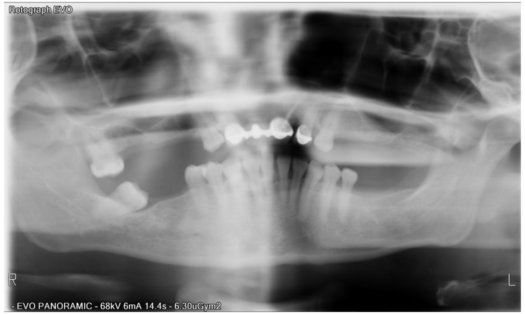


Image source: UFBA-UESC Dental Images dataset, GLDP dataset

Different convolutional neural networks were developed as modeling solutions

Mask R-CNN

	Mask R-CNN	You Only Look Once (YOLO)
Advantages	• Easier to compare specific, closer objects	• Addresses occlusion • Ease of generalization • Smaller framework
Disadvantages	• Performs per-pixel comparison • Struggles with overcrowded or overlapping objects	• Low recall and more localization error • Struggles detecting close, smaller objects

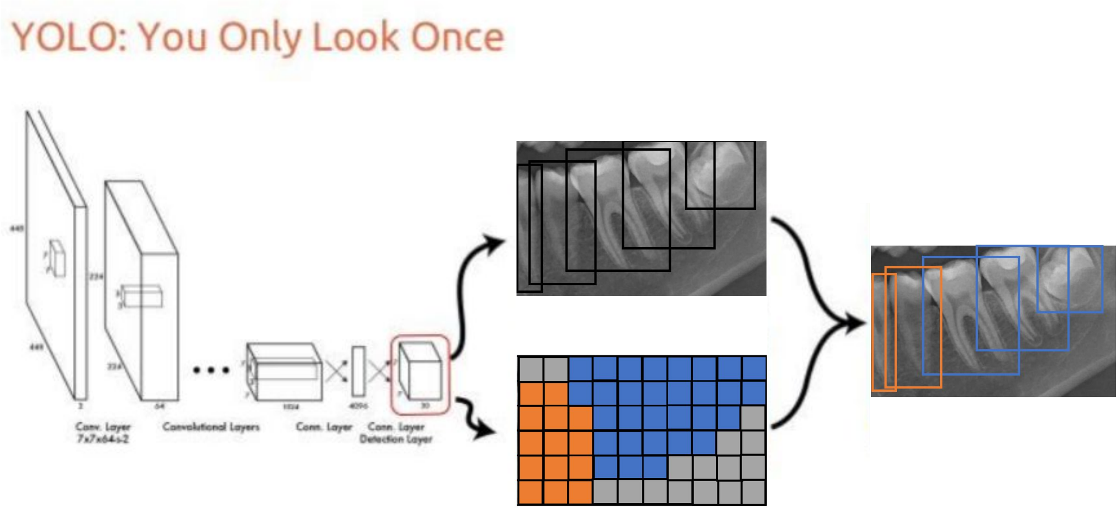
Object Detection

YOLOv5

Images source: https://www.geeksforgeeks.org/yolo-you-only-look-once-real-time-object-detection/, http://vision.stanford.edu/teaching/cs231b_spring1415/slides/ssearch_schuyler.pdf

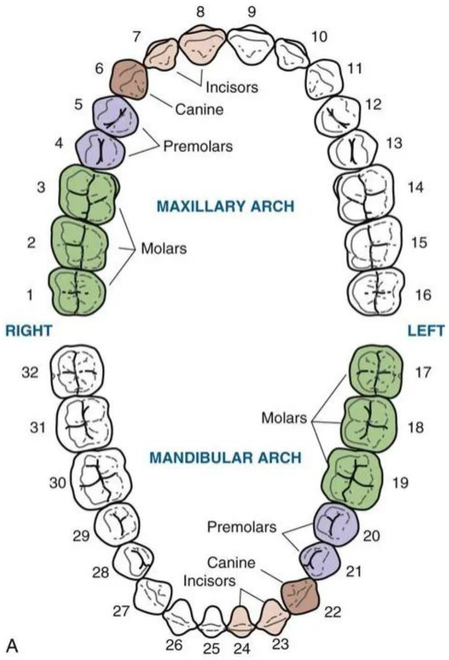
Building a model with YOLOv5 for tooth detection

- Utilized transfer learning for our model's initial weights
- Given x-ray masks, extracted bounding boxes and converted to YOLO label format
    - YOLO labels must be normalized
- Images normalized for corresponding YOLO labels



Images source: https://www.semanticscholar.org/paper/Surface-Defect-Detection-Using-YOLO-Network-Hatab-Malekmohamadi/08f1c9578854e8ca3425f8d616cebe1fa0f10adf

The model was further improved to classify tooth type as well as tooth detection

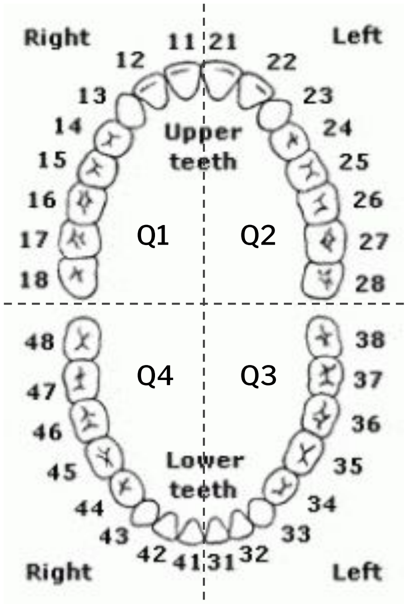


- Classified through detections of the tooth detection model
- Data is automatically assigned to one of four tooth types (classes)
- Fine-tuned through hyper-parameter evolution and non-maximum suppression

Images source: https://coreem.net/core/dental-trauma/

We tested three different algorithms to apply tooth numbering and identify missing teeth

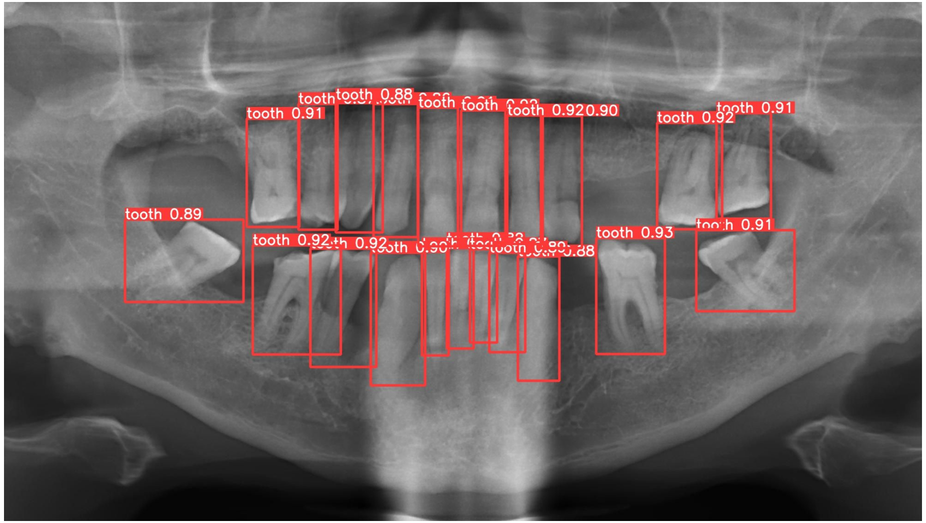
- Maximum Numbering:
  - Rule-based numbering using information about quadrant and tooth type
- Bayesian Neural Network:
  - Use X-Y coordinates of teeth to train network to estimate location on new x-rays
- Minimum Euclidean Distance:
  - Calculate minimum distance between bounding boxes to estimate tooth numbers



Images source: https://www.teethfaq.com/what-tooth-numbers-mean/

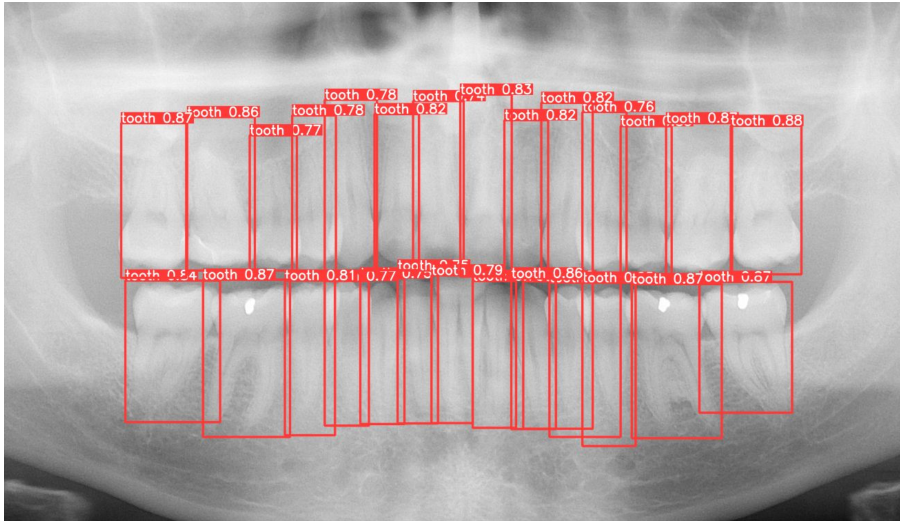
The first model detected all tooth instances with varying degrees of confidence score

Good image quality



Average confidence = 89.7%

Low image quality

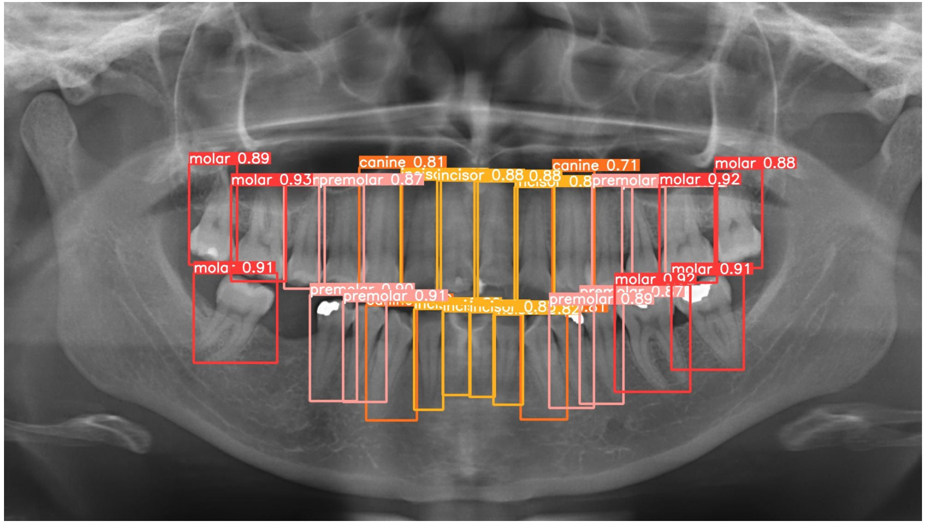


Average confidence = 80.4%

Confident = intersection over union (IOU) between predicted box and the ground truth

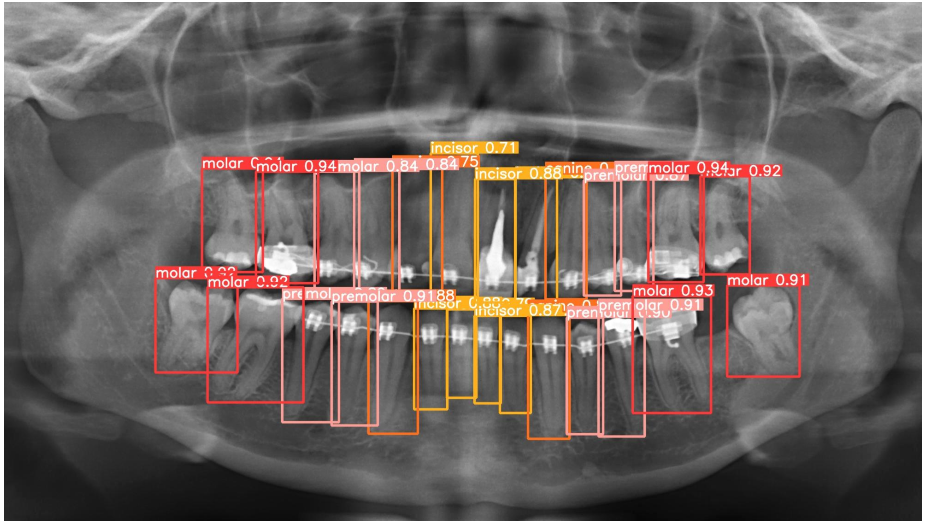
The second model was able to consistently detect and classify all teeth according to tooth type

With dental restoration and missing teeth



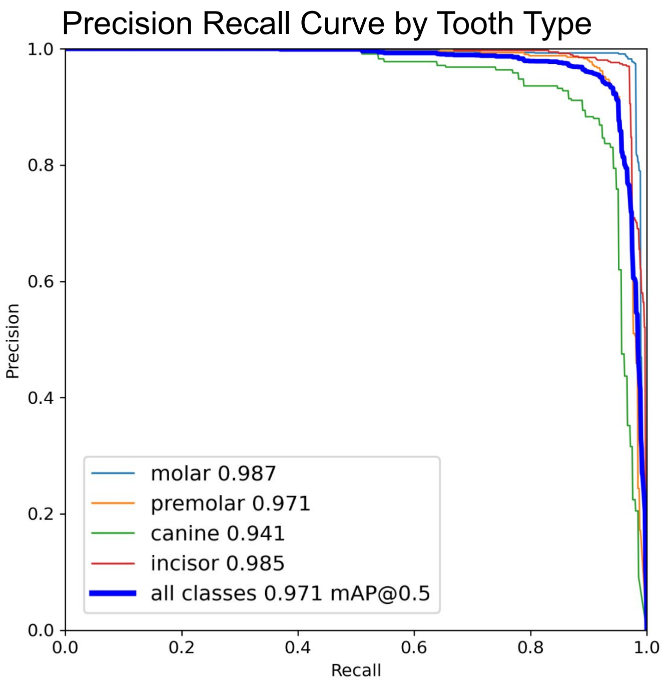
Average confidence = 86.5%

With dental appliance



Average confidence = 87.3%

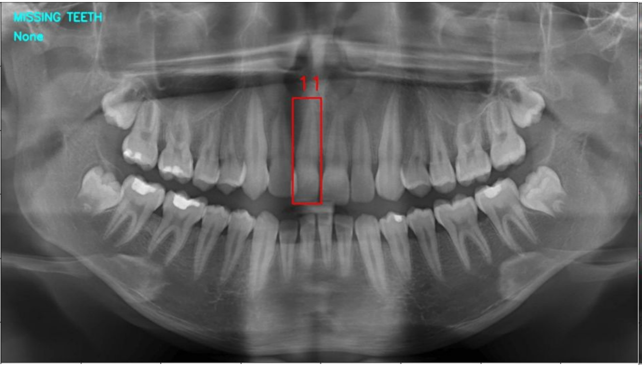
The model performed strongly for identifying all four tooth types



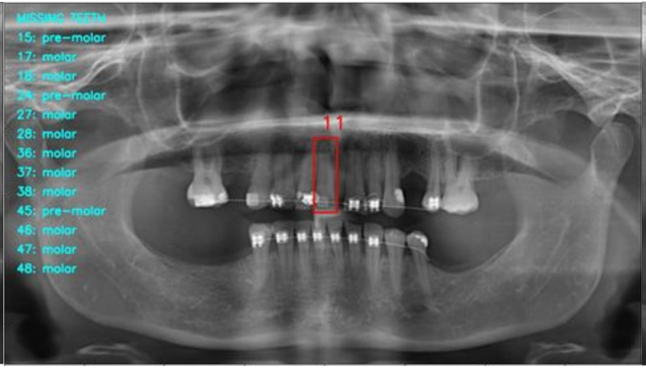
The maximum numbering model performed the best for tooth labelling and missing tooth identification

- Maximum Numbering - 91.5% accuracy
- Bayesian Neural Network - 73% accuracy
- Minimum Euclidean Distance - 65% accuracy

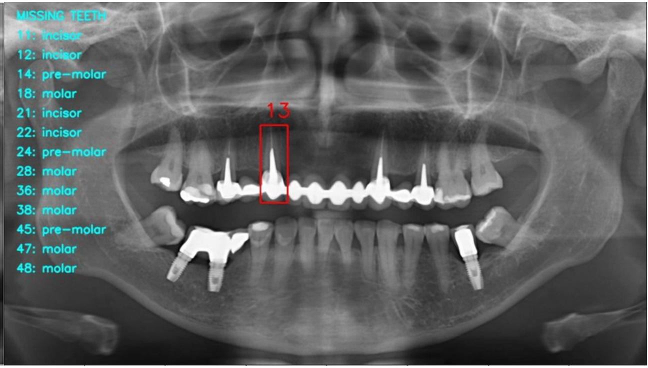
All 32 teeth present



Missing teeth + Dental appliance



Missing teeth + Implants and Restorations



Images source: GIFs created using https://gifmaker.me/

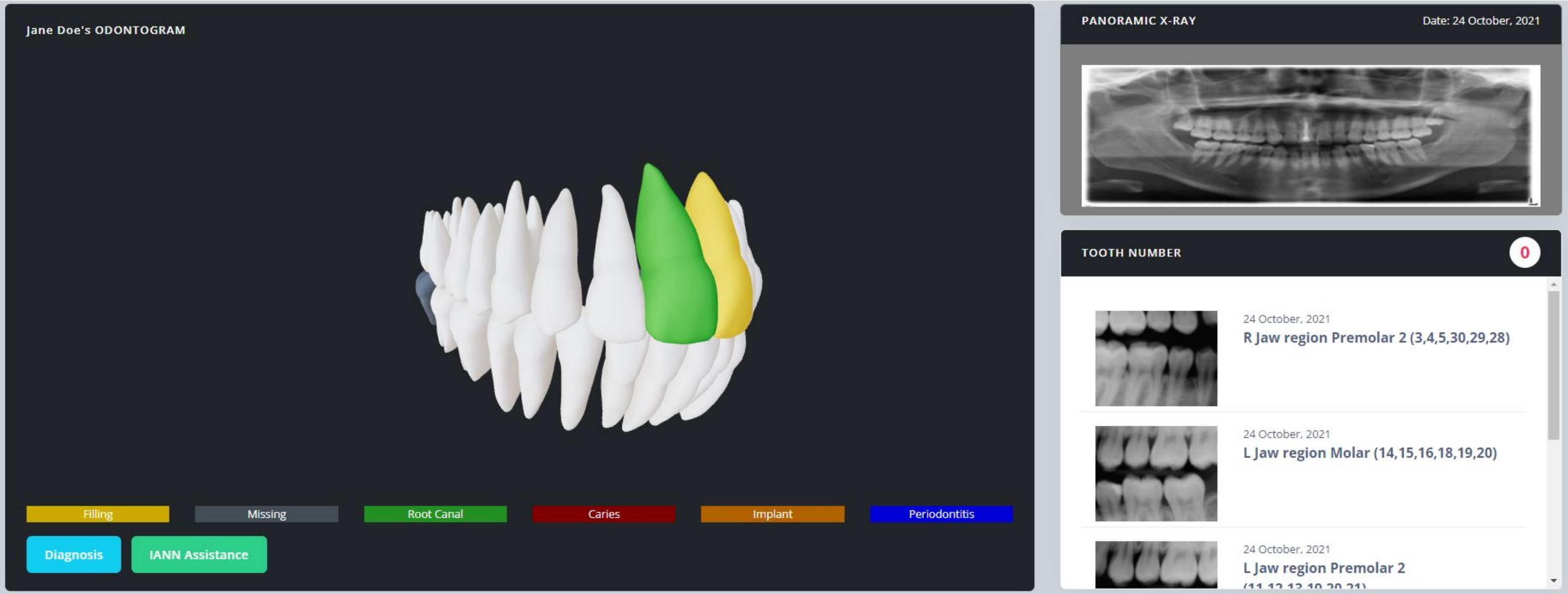
Our model could be expanded to include labelling bitewing x-ray images

Bitewing X-ray Image Showing Molars and Premolars on the Left Side of the Mouth

- Bitewing dental x-ray images offer a clearer view of specific teeth that can lead to early problem detection
- This can be combined with panoramic images to improve detection of tooth type and location information

Images source: Great Lake Dental Practices Dataset

Our methodology enabled IANN to conduct further research into dental AI



Images source: https://www.oregondentist.com/Blog/Post/The-Difference-in-Digital-Dental-X-Rays

Thank you!

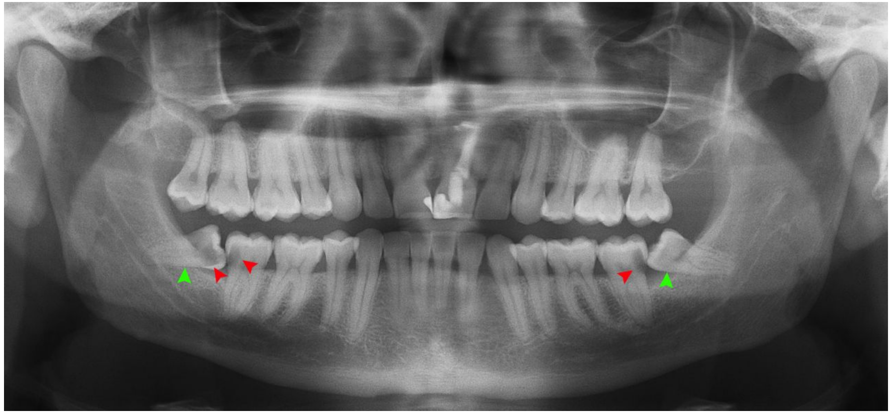
Special thanks to Utku Pamuksuz and Batuhan Gundogdu for helping throughout the process

Questions?

Appendix

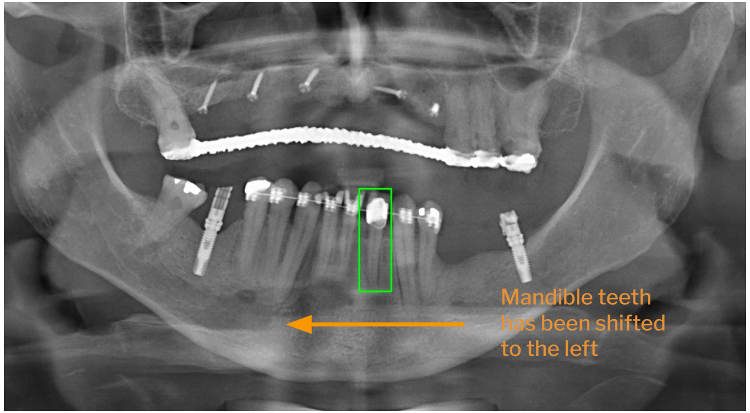
The value of instance segmentation of teeth

Collision



Identify tooth collison and misoriented wisdom teeth

Orthodontics

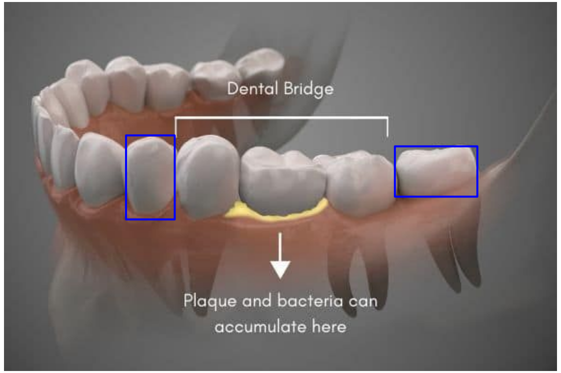


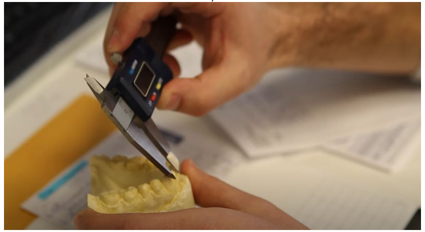
Automatically detect orthodontics and identify the shifting and the missing teeth

Images source: https://www.wikiwand.com/en/Impacted_wisdom_teeth

Dental AI in fixed partial denture procedures

Fixed Partial Denture (Bridge)





Deep Learning Approach:
1. Provides instant results for dentist
2. Reduces clinical visits for patients
3. Cheaper in labor and medical supply cost

Tradition approach:

1. Takes at least 2 weeks to measure the tooth distance after patient's first dental visit

2. Requires multiple dental visits for patients

Images source: UFBA-UESC Dental Images dataset, Lapointe dental centres, Electric Teeth, https://www.youtube.com/watch?v=i3X90DQ5Vio, How To Care For Your Dental Bridge - Dental Studio

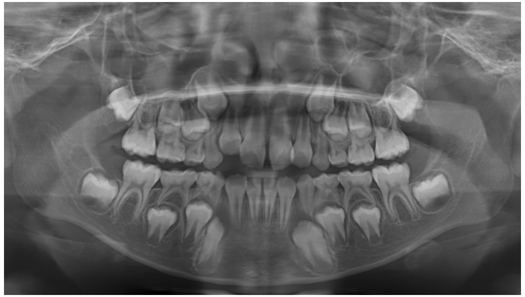
UFBA-UESC Dental Images dataset categories

Category	Description	Number of Images	Average Number of Teeth
1	Images with all the teeth, containing teeth with restoration and with dental appliance	73	32
2	Images with all the teeth, containing teeth with restoration and without dental appliance	220	32
3	Images with all the teeth, containing teeth without restoration and with dental appliance	45	32
4	Images with all the teeth, containing teeth without restoration and without dental appliance	140	32
5	Images containing dental implant	120	18
6	Images containing more than 32 teeth	170	37
7	Images missing teeth, containing teeth with restoration and dental appliance	115	27
8	Images missing teeth, containing teeth with restoration and without dental appliance	457	29
9	Images missing teeth, containing teeth without restoration and with dental appliance	45	28
10	Images missing teeth, containing teeth without restoration and without dental appliance	115	28

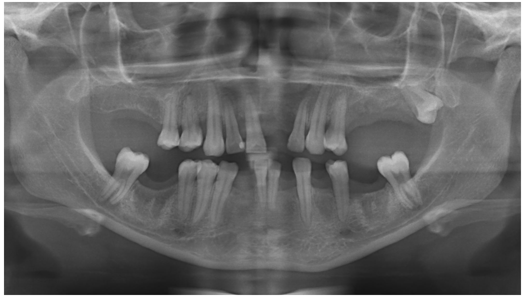
The UFBA-UESC Dental Images dataset was subdivided into ten different categories

32 teeth

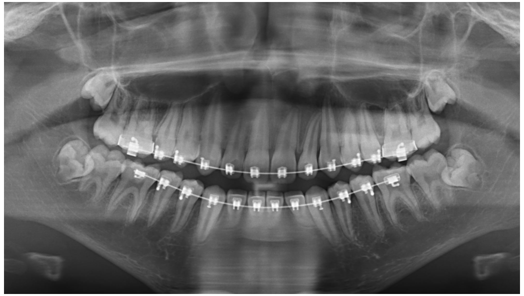
More than 32 teeth



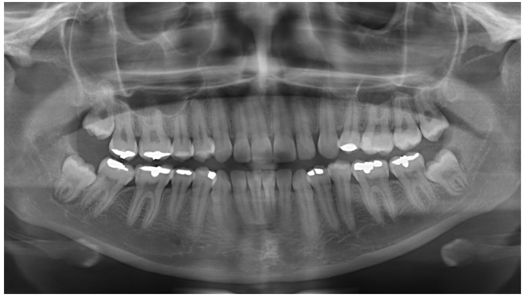
Less than 32 teeth



Dental appliance (e.g. braces)



Dental restoration (e.g. fillings)



Dental implant (e.g. fake teeth)

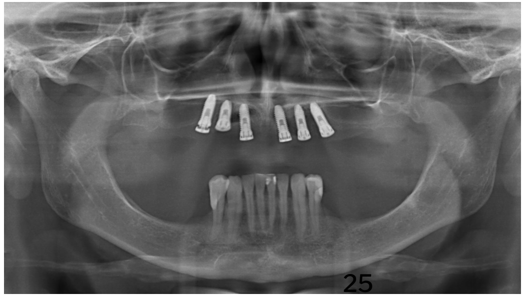


Image source: UFBA-UESC Dental Images dataset

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Convolutional Neural Network Framework (YOLOv5)

- 3 main foundations in the framework
  - Feature extraction
  - Generate feature pyramids network to perform aggregation on the features
  - Generate predictions from the anchor boxes for object detection
- 2 choices for training
  - Activation and optimization
  - Loss function

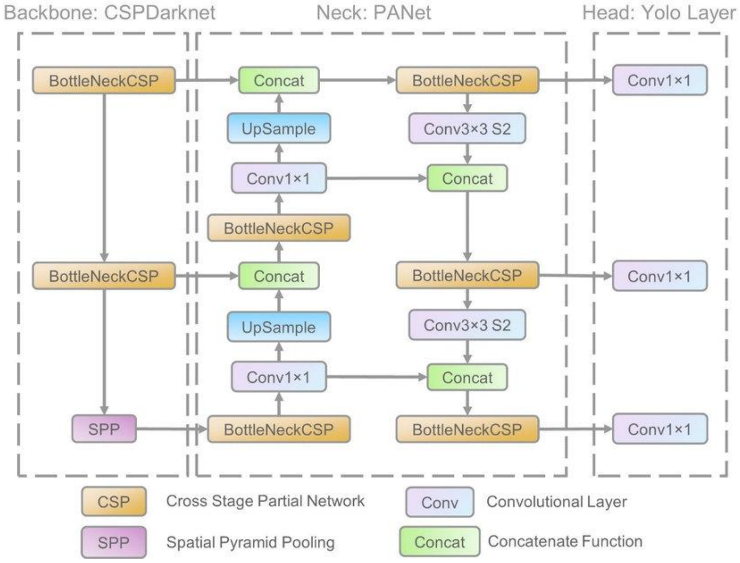


Image source: https://www.researchgate.net/publication/349299852_A_Forest_Fire_Detection_System_Based_on_Ensemble_Learning

Tooth detecting and type classification - double bounding box

Double bounding box - before non-maximum suppression is applied

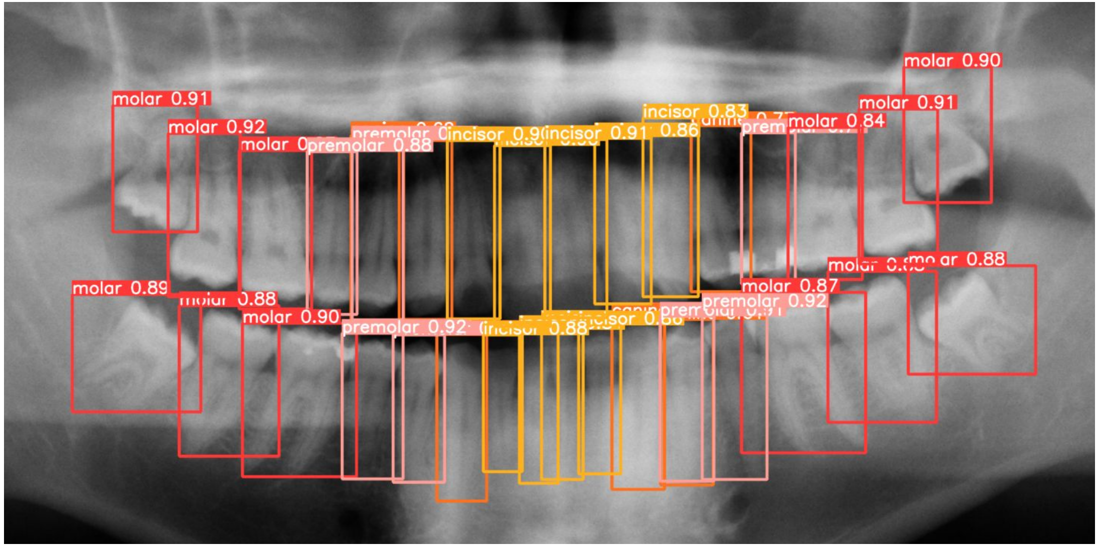
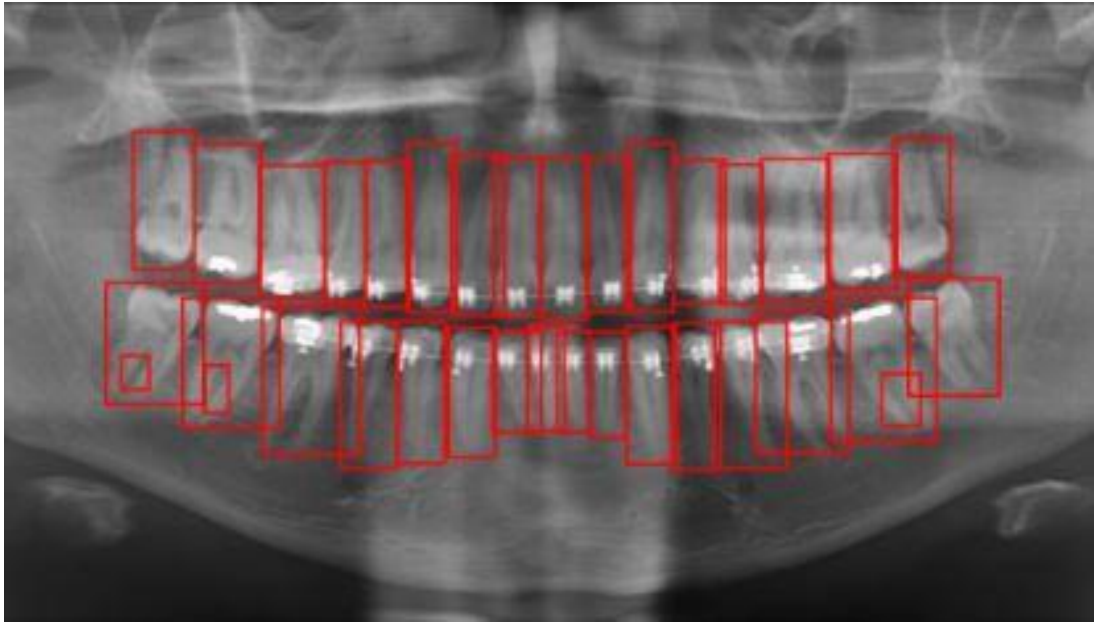


image cropped for larger view

Mask R-CNN

Mask R-CNN Segmented X-ray with Incorrect Bounding Boxes



“Perfect” tooth detection and classification

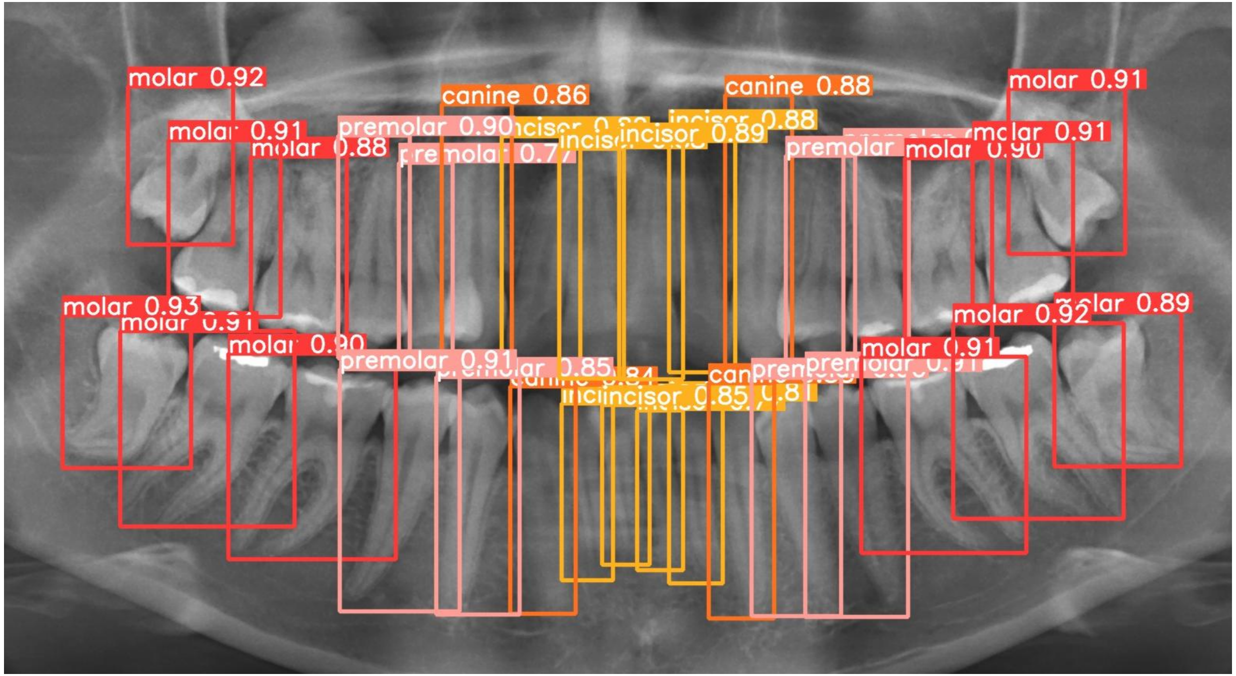


image cropped for larger view

False tooth detection and classification (detecting implant as tooth)

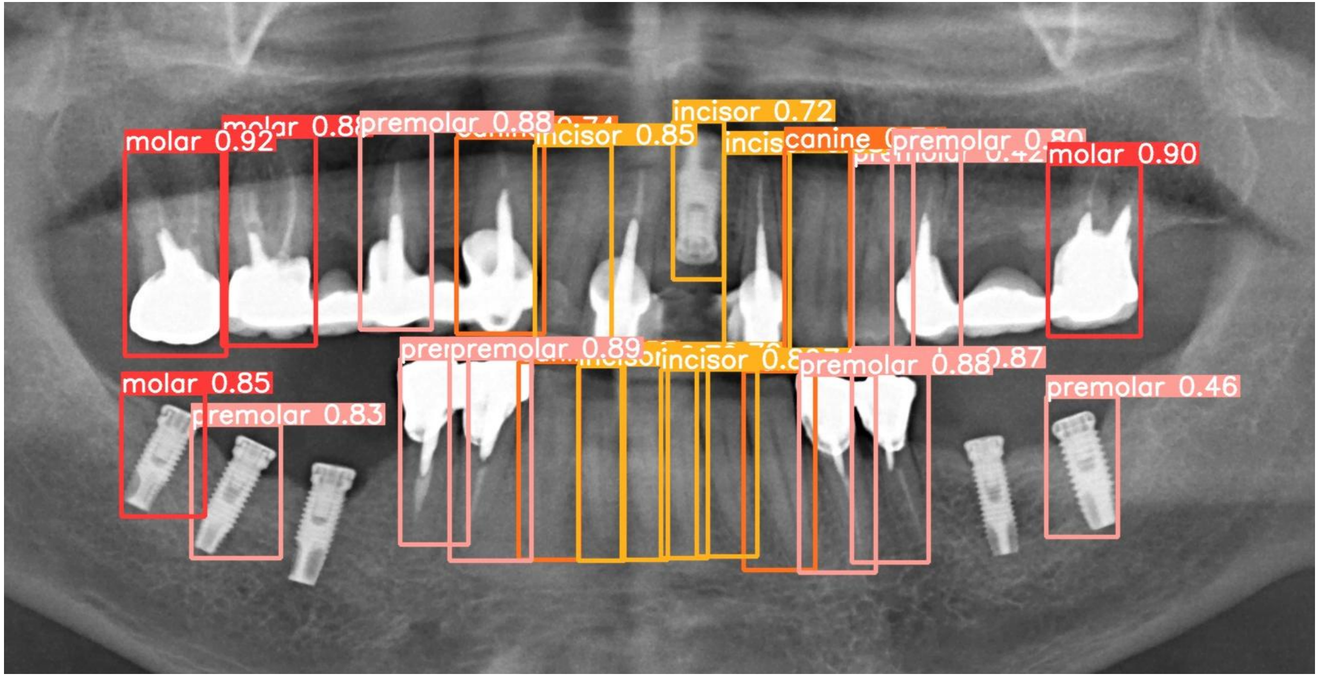
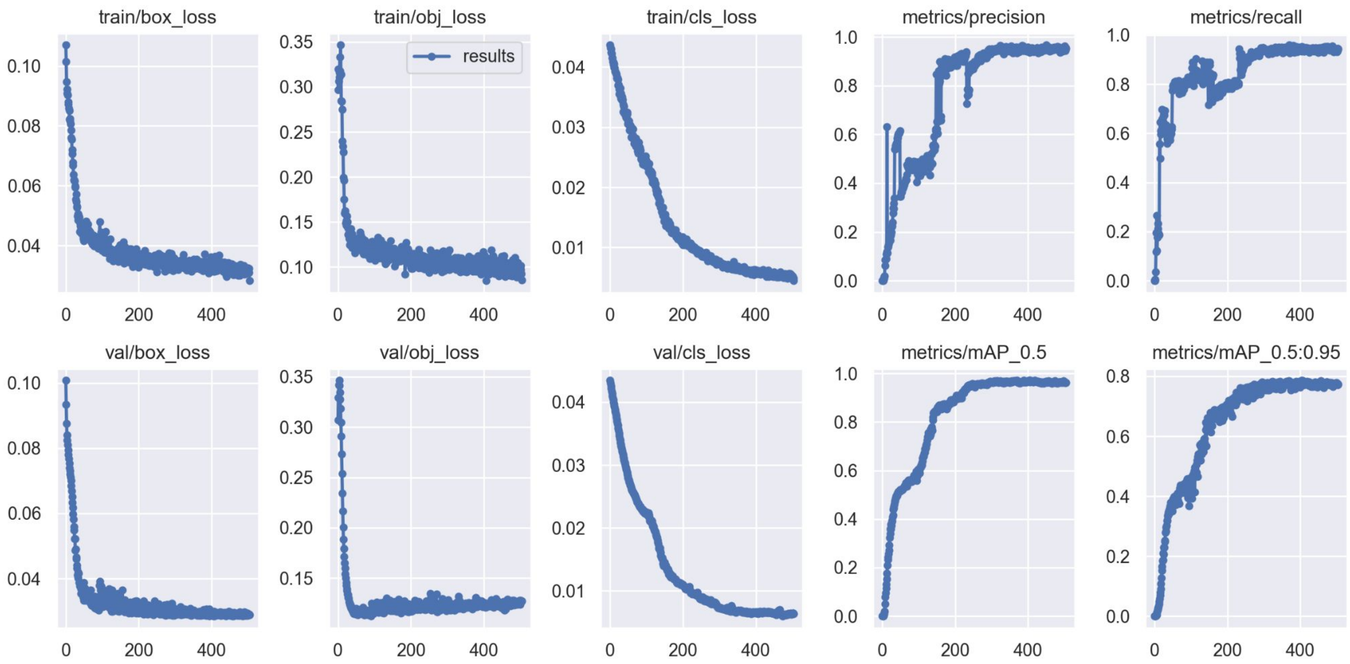


image cropped for larger view

Tooth classification model results



The final model was integrated with Flask to produce a GUI that can input a dental x-ray and return it labelled

Github link

https://github.com/joechudzik/IANN-image-segmentation

Potential questions from judges

1. How did we get the original bounding boxes that we used to train YOLOv5?
2. How did we get the original trained weights to train YOLOv5?
3. How does the model perform on a bad x-ray vs a good x-ray?
4. Why four classes, not 32 classes?
5. What was the major bottleneck/roadblock to achieve this outcome?
6. How generalizable is your model to different regions in the world
7. What is hyperparameter evolution and non-maximum suppression?
8. How do you measure numbering accuracies?
9. Why did the other 2 approaches not work while rule based worked?
10. What more can be accomplished if you had more time for this project?