Dental Implant Brand Detector

An AI-based solution that makes dentists work
more efficiently

Inference Analytics Neural Network

Meet Our Team

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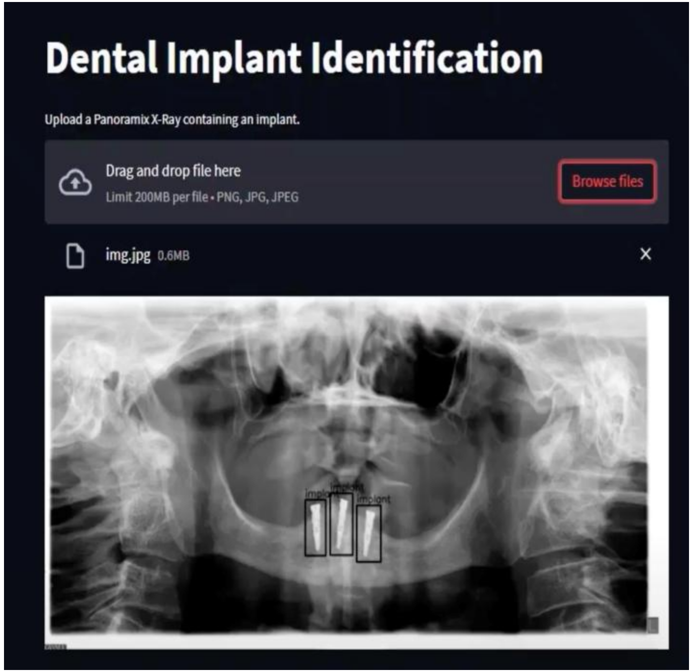
Executive Summary

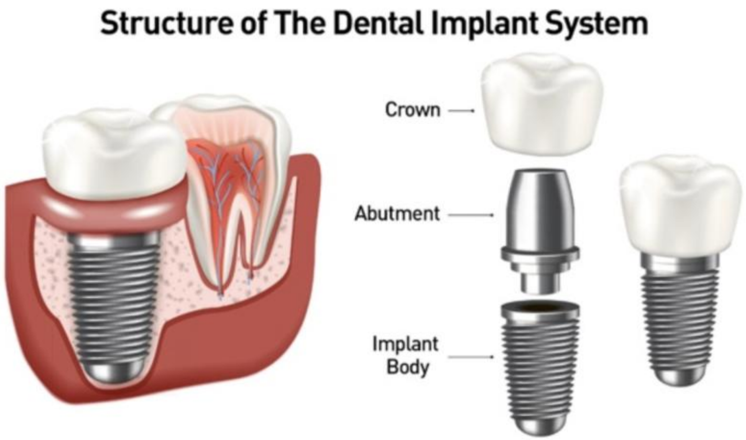
- We developed an AI solution which takes a panoramic x-ray and identifies the implant brand for dentists in real time.
- Though the data is limited, our AI detector achieves a desirable accuracy.
- Our AI ensemble solution is estimated to save 30 minutes per consultation session for dentists.
- The App is ready to deploy!



A Dental Implant is a replacement of tooth root

- The dental implant surgery is a procedure that replaces tooth roots with metal, screw-like posts and replaces damaged or missing teeth with artificial teeth that look and function much like real ones.

- The average lifespan of a dental implant is approximately 10 to 15 years



Business Problems

Task

- ❖ For patients who have implants already and require further treatment or replacement, identifying brands of the existing implants on images is a vital task to the dentists

Problems

- ❖ Patients usually don’t know the brand of their dental implants.
- ❖ Even if the patients know their brands, they are likely to forget the name of brand years later when a replacement is needed.

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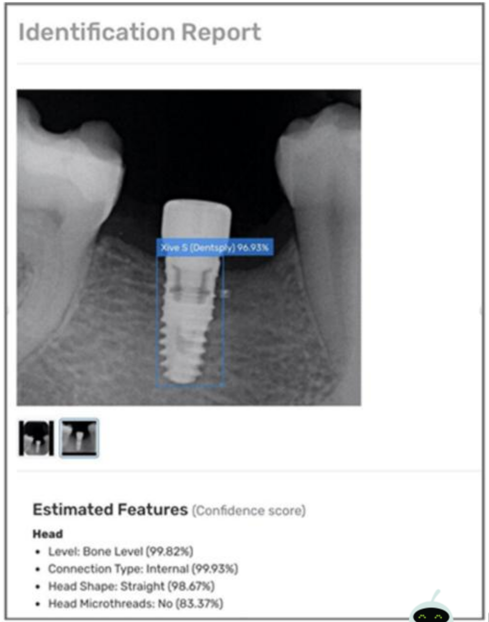
Deep Learning based approach could replace the manual searching process

Current solution

❖ Dentists are currently searching for the origin of the implant manually and developing a treatment plan once they find it.



Desired solution

❖ Automate this process to save medical professionals' time
❖ Solution should automatically detect implants in an x-ray image and predict the brands of the implants

Data are X-Ray Images including Panoramic and Bitewing

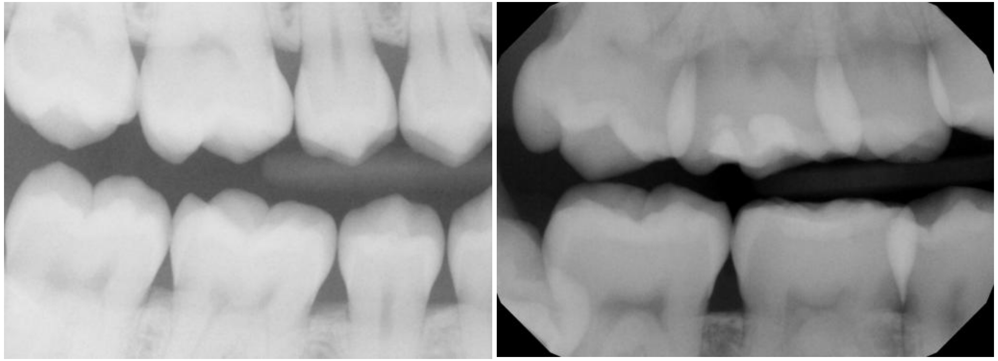
Providing Company: Great Lake Dental

Data Format: X-ray Images, YOLO labeled data

Examples:

Panoramic

Bitewing



8 Classes are Labeled and 'Existing-Implant' is the main focus

YOLO (You Only Look Once) Labeled Data:

8 Classes in Total:

Class Name	Label Number
existing - filling	0
existing - root canal treatment	1
existing - implant	2
caries low risk	3
caries moderate risk	4
caries high risk	5
periodontitis	6
crown	7

Ready for Processing:
Almost 2 million panoramic X-Rays/bitewing/fmx/photo

Annotated & Ready for Training:
30 thousand panoramic X-Ray

Scheduling Optimization:
400 implant labeled images along with Dental Clinic's database records with 11 brands in total

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Solutions to Three Main Challenges on Data

1. Given limited number of labeled implants images (<400) available, it is not sufficient for deep learning algorithms.
   Solution: Use YOLO to label the unlabeled images to get more samples

1. A lot of X-ray images are blurry or overexposed.
   Solution: Manually throw out bad quality images

1. Dentists will reshape each implant before planting. So it will look different even though they might be exactly the same implant.
   Solution: Manually categorize the implants

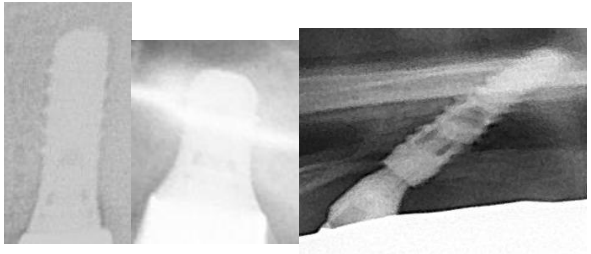

Figure 1.Blurry, Overexposed implant images

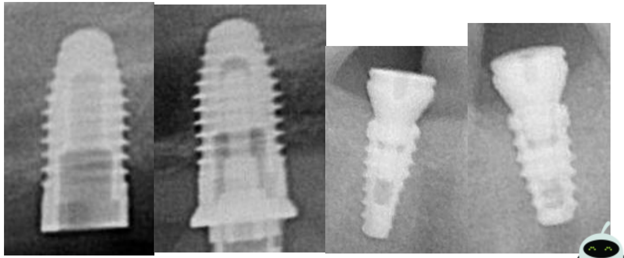

Figure 2. Hard to tell whether same or different brand

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The Analytical Plan Follows a Stepwise Manner and Attempt Different Techniques

Model for detect and label the implants locations

Build the final clustering model with the complete dataset

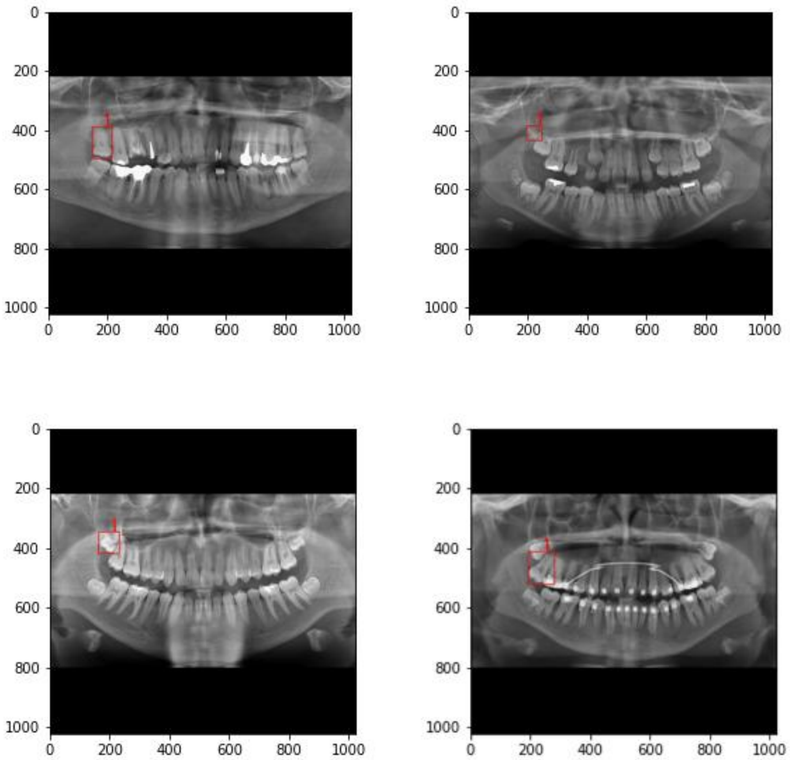
Build Model that Detect Implants in the X-ray Images

Compare Models that Detect Brands of Implants

Deliver demo that streamline the whole process

Compare different models and evaluate their performance

YOLO Labeling technique



Procedures:

1. Use YOLO to detect each tooth in the X-ray
2. Iterate through every tooth detected
3. Label each tooth using a box for future analysis

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The size of available image data is tripled by implementing YOLO for implant detection

To filter the data and locate implants, we train YOLO model with known implant images. Then use the trained model to find the unlabeled implants.

Use **Intersection Over Union (IOU)** as our metric to train the model, which is Area of overlap between predicted bounding box and true bounding box

Increased our available implants image data **from 390 to 996.**

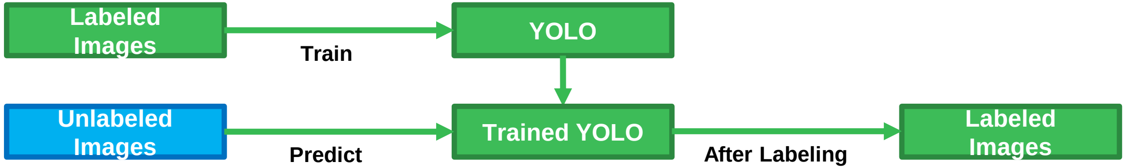

Figure 1. X-ray Images Before Labeling

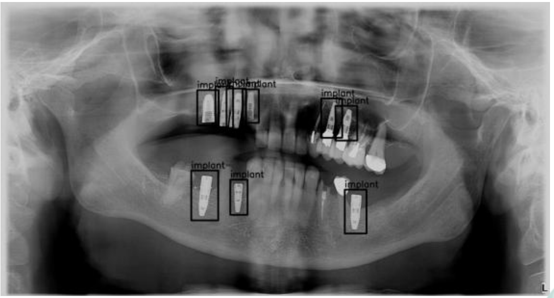

Figure 2. X-ray Images After Labeling

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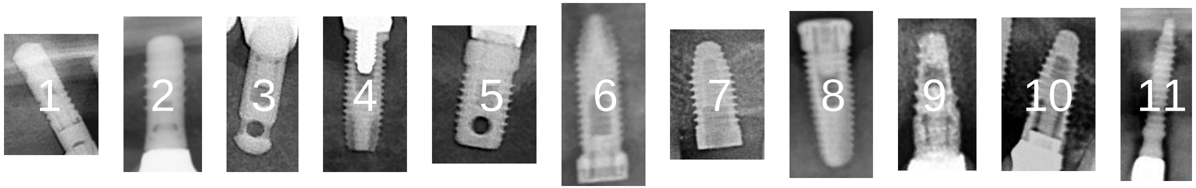
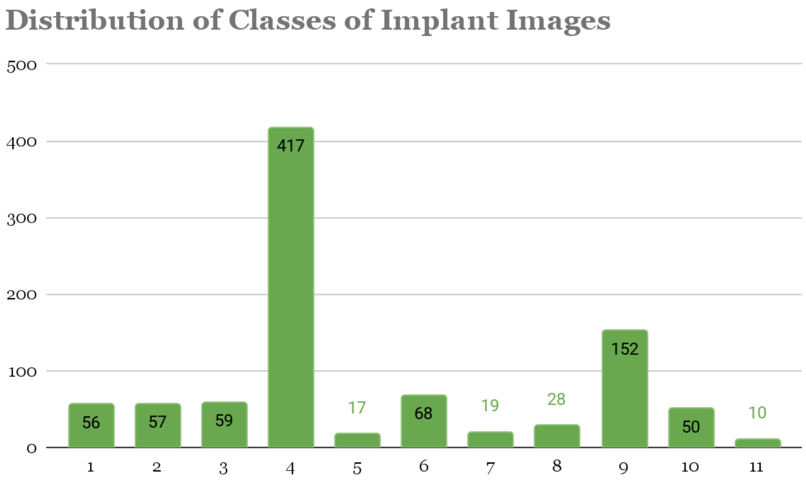
11 Classes are Manually Categorized for the Training Purpose

Manual categorization to **11** classes





We manually categorize our implants into 11 brands, trying to gather as many data as possible

We have a total of 933 implant images in 11 classes. However, the data are imbalanced

Models 1 : K-Means Clustering did not generate promising results

#1 K-Means Clustering

Procedure:

1. Feature extraction with pretrained VGG16
2. Use K-Means clustering model with 11 classes.

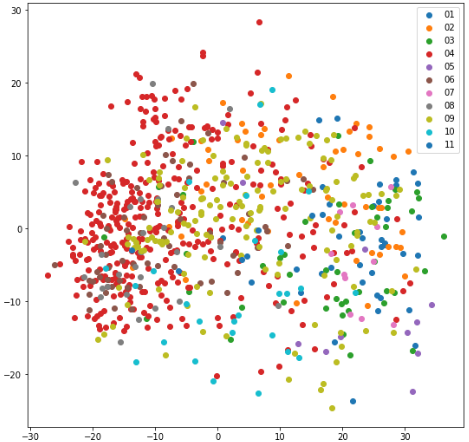


Figure 1. Cluster colored with true classes

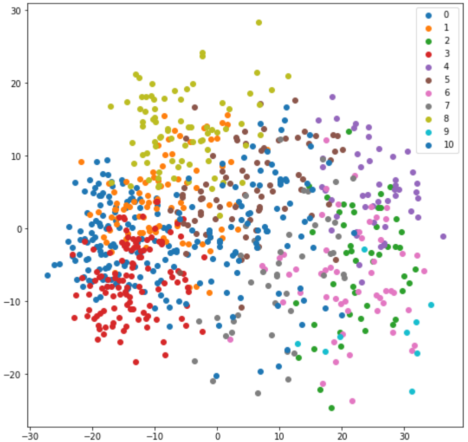


Figure 2. Cluster colored with predicted classes

Results:

It did NOT give us a good cluster.

The cluster on the right (Cluster from K-Means) is very different from the cluster on the left (True Class)

Decision:

NOT to go forward with it

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Models 2 : EfficientNet was associated with low accuracy and imbalanced issue

#2 Pre-trained EfficientNet Model

Procedure:

Use Pre-trained EfficientNet to predict classes

Apply data augmentation that create more sample by flipping, resizing the images.

Results: **23% Accuracy with heavy classes imbalance**

On the left (Predicted Results), only class 4 and 9 have lots of correct prediction which is due to over 50% of our training samples are from class 4 and 9.

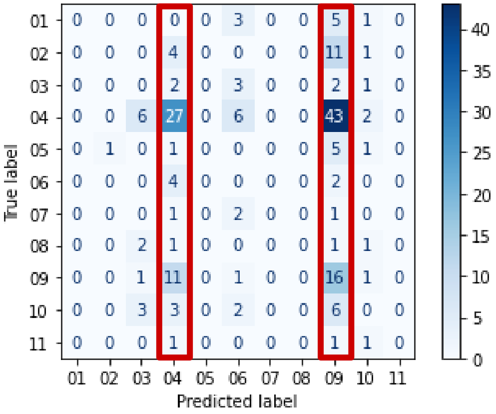


Figure 1. Confusion Matrix – Most of the predictions are class 4 and 9

Classification Report

	precision	recall	f1-score	support
01	0.00	0.00	0.00	9
02	0.00	0.00	0.00	16
03	0.00	0.00	0.00	8
04	0.49	0.32	0.39	84
05	0.00	0.00	0.00	8
06	0.00	0.00	0.00	6
07	0.00	0.00	0.00	4
08	0.00	0.00	0.00	5
09	0.17	0.53	0.26	30
10	0.00	0.00	0.00	14
11	0.00	0.00	0.00	3
accuracy			0.23	187
macro avg	0.06	0.08	0.06	187
weighted avg	0.25	0.23	0.22	187

Figure 2. Classification Report – Class 4 and 9 has much better precision and recall than other classes

Models 3 : Siamese Network is more robust to class imbalance and require less training data

#3 Siamese Network

Siamese Network is introduced since it is able to use very small number (>6) of images to achieve accurate predictions

<u>Model Feature:</u>

Siamese Network, instead of learning all the features of the classes, learns to differentiate between classes

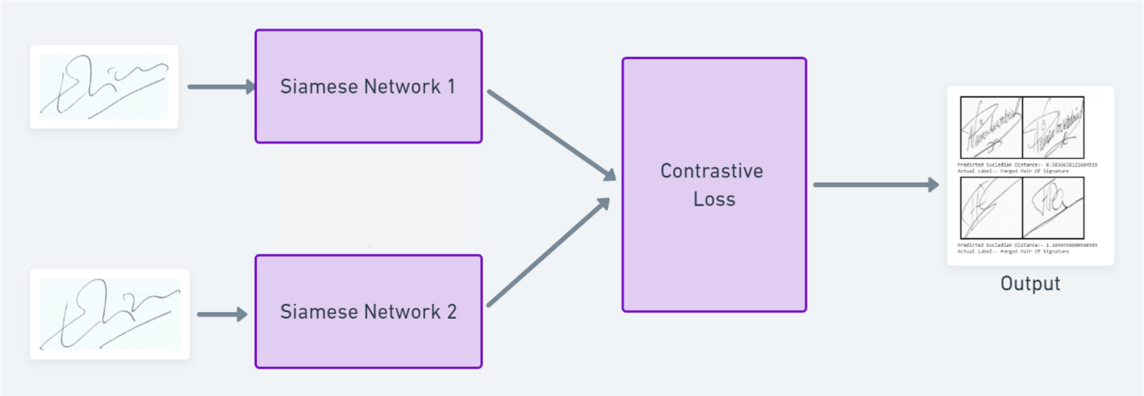


Figure 1. Siamese Network – Signature Verification Example

Models 3 : Dissimilarity Scores from Siamese Network

#3.1 Siamese Network example output

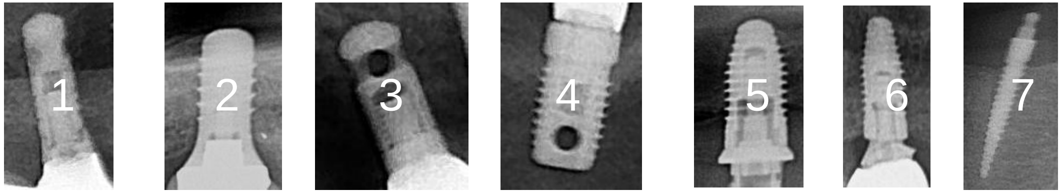
Siamese Network only provides similarity score between two images.

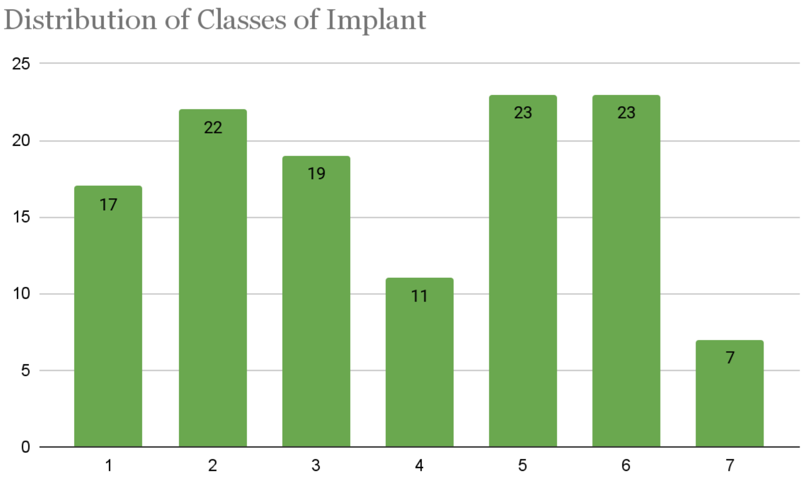
<u>Following steps to predictions</u>

1. Compare a test image to every train images we have and get the dissimilarity scores for all such pairs.
2. Get an average dissimilarity score grouped by classes.
3. The class with the best score will be the top prediction.

7 Classes are Manually Categorized for the Training Purpose

Manual categorization to **7** classes





Every implant from different classes have distinct characteristics. Untrained human can tell apart implants that are from different classes.

Total 143 images gives us ~10000 unique image pairs for training Siamese Network

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Models 3 : Re-apply Siamese Network with 7 Manually Categorized Classes

#3.2 Siamese Network Evaluation

Recap on how we make prediction:

1. Compare a test image to every train images we have and get the similarity scores for all.
2. Get an average dissimilarity score from each class.
3. Classes with the best scores will be the top predictions.

Classes	1	2	3	4	5	6	7	Overall
Accuracy	47%	5%	5%	9%	72%	38%	14%	**31.5%**
Top 2 Accuracy	77%	23%	5%	9%	91%	95%	14%	**58.7%**

Metrics and evaluations

Metrics:

1. For YOLO model, Intersection Over Union (IOU) ,which is a standard metric for evaluating object detection algorithm, is used to evaluate our YOLO model
2. For multiclass classification model, we use both accuracy and top-2 accuracy to evaluate our clustering model

Metrics	
Intersection Over Union (IOU)	Area of overlap/Area of union (between predicted bounding box and true bounding box)
Accuracy	Out of all predicted as class A, how many really belong to class A?
Top-2 Accuracy	If the true brand of the implants is within our predicted top 2 most probable brands, we consider it as correct prediction.

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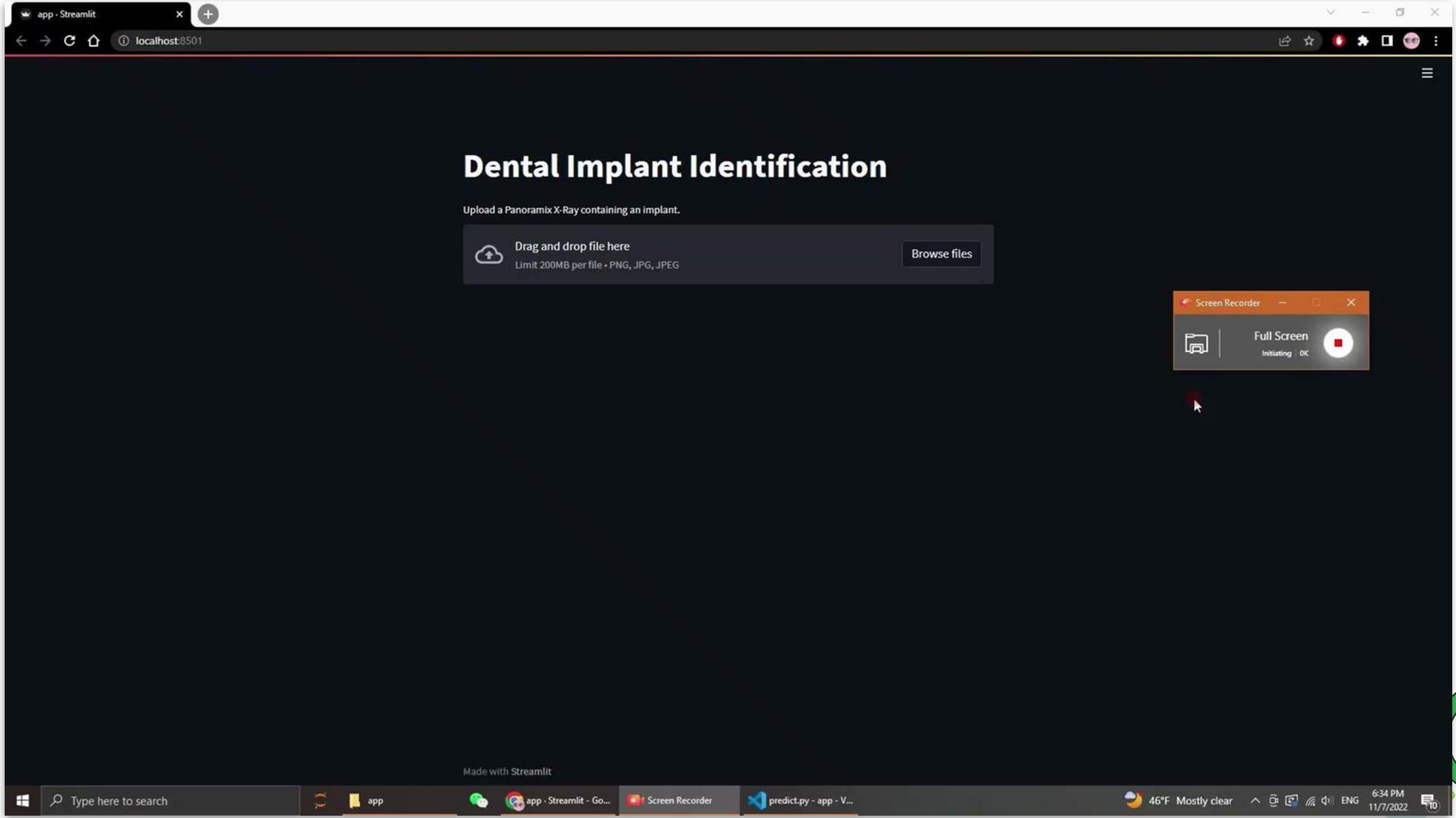
Final Product Demo



Final Conclusion

Conclusion

Our data was not enough for training the K-Means or pre-trained deep learning model. Siamese Network could overcome this problem and performed the best out of all models.

Deliverable

Fully functional implant identification app based on Siamese Network model

Next Step

1. In the future, the model's accuracy could be improved if we have access to higher quality data (implants' brands labeled by medical professionals, etc.)
2. Similar model could be used for training other AI for dentists. (e.g., detecting the existing tooth filling material when operating a tooth filling replacement)

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Thank You

Any Questions?

Contrastive Loss Function where

- Dw is is defined as the euclidean distance between the outputs of the sister siamese networks
- Y indicating whether the two inputs are from the same class (0 means same classes)
- m is a margin value which is greater than 0. Having a margin indicates that dissimilar pairs that are beyond this margin will not contribute to the loss:

$$(1-Y)\frac{1}{2}(D_W)^2 + (Y)\frac{1}{2}\{max(0, m - D_W)\}^2$$