# visual analysis

July 29, 2025

# 1 Visual Analysis of Dental Radiography Dataset

This notebook performs comprehensive exploratory analysis and visualization on the **Dental Radiography** dataset available at Kaggle.

## 1.1 Dataset Description

The dataset contains dental radiograph images and corresponding YOLO-style annotations for various oral conditions (e.g., caries, crown, implants). It's suitable for object detection, image classification, and semantic segmentation tasks in dental AI applications.

#### 1.2 Notebook Overview

## 1.2.1 1. Annotation Parsing & Preprocessing

- Load YOLO-format annotations using label\_parser.py
- Group bounding boxes, detect duplicated labels per tooth, and filter single/multi-class images

#### 1.2.2 2. Class Distribution Analysis

- Use class stats utils.py to extract label counts and frequency of each class
- Visualize number of annotations and unique images per class in train, val, or test splits

#### 1.2.3 3. Annotation Visualization

- Use annotation\_visualizer.py to display bounding boxes:
  - Single-class examples
  - Multi-class images
  - Grouped teeth with overlapping annotations (multi-label situations)

#### 1.2.4 4. Ratio-Based Image Analysis

- Compute and visualize:
  - Missing Teeth Ratio from segmentation masks
  - Darkness Ratio from grayscale intensity
- Display histograms and heatmaps to explore data distribution

## 1.2.5 5. Semantic Segmentation with SegFormer

- Apply pretrained model vimassaru/segformer-b0-finetuned-teeth-segmentation via segmentation\_utils.py
- Segment X-rays and visualize the teeth areas

## 1.2.6 6. Feature Embedding of Images & Masks (No Clustering)

- From mask\_clustering\_analysis.py:
  - Extract RGB color histograms
  - Apply PCA, t-SNE, and UMAP to obtain image-level embeddings
  - Visualize most distinct images along each embedding dimension

#### 1.3 Dataset Source

Kaggle: Dental Radiography Dataset

#### 1.4 Code Modules

| File   | Purpose   |
|--|---|
| label_parser.py  | Parses YOLO annotations, groups teeth, checks label consistency   |
| <pre>class_stats_utils.py annotation_visualizer.py</pre> | Extracts and visualizes class and image frequencies<br>Shows annotated examples: single/multi-class and |
|  | grouped boxes   |
| segmentation_utils.py                                    | Applies SegFormer model to X-ray images   |
| mask_clustering_analysis.py                              | Embeds image and mask features via color histograms (no clustering)                                     |

```
[1]: # Imports
import pandas as pd
from label_parser import load_annotations_csv, get_class_frequencies,__
filter_images_by_num_classes

# Path to annotations
csv_path = "/Volumes/L/L_PHASO077/dental_radiography/train/_annotations.csv"

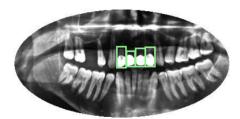
# Load annotations and show label stats
df = load_annotations_csv(csv_path)

# Show class frequency
print(" Class Frequency:")
print(get_class_frequencies(df))
```

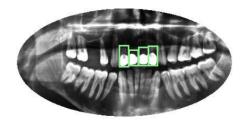
```
Class Frequency:
    Fillings
                       5242
    Implant
                       1784
    Cavity
                        576
    Impacted Tooth
                        428
    Name: count, dtype: int64
[2]: from annotation_visualizer import (
         visualize_single_class_examples,
         visualize_multi_class_examples,
         group_bounding_boxes,
         visualize_grouped_boxes
     )
     class_colors = {
             "Implant": "skyblue",
                                        # Light and clear blue
# Soft and distinguishable green
             "Fillings": "lightgreen",
             "Impacted Tooth": "orange", # Bright orange
             "Cavity": "purple"
                                           # Strong and distinct purple
         }
     main_path = '/Volumes/L/L_PHAS0077/dental_radiography/'
     main_train_path = main_path + 'train'
     file_path = main_train_path+'/_annotations.csv'
[3]: df_flat = []
     for _, row in df.iterrows():
         for label, bbox in zip(row["Labels"], row["BBoxes"]):
             df_flat.append({
                 "filename": row["Image"],
                 "class": label,
                 "xmin": bbox[0],
                 "ymin": bbox[1],
                 "xmax": bbox[2],
                 "ymax": bbox[3]
             })
     df_flat = pd.DataFrame(df_flat)
[4]: # Call each visualization as needed
     visualize_single_class_examples(df_flat, main_train_path, class_colors)
```

# Images for Class: Fillings

Class: Fillings

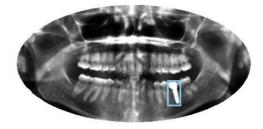


Class: Fillings

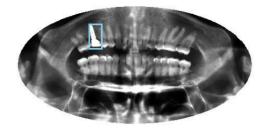


Images for Class: Implant

Class: Implant

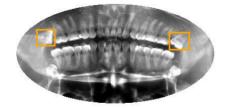


Class: Implant

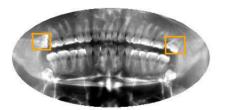


Images for Class: Impacted Tooth

Class: Impacted Tooth



Class: Impacted Tooth



## Images for Class: Cavity

Class: Cavity



Class: Cavity



#### Images with Multiple Classes and Bounding Boxes

Image: 0911\_jpg.rf.11ba7bcbbd3056174e462824c85bcdd8.jpg

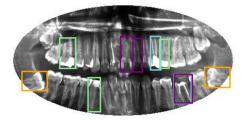
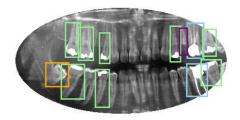


Image: 0974\_jpg.rf.1106191cfb2fa2d640fa75593eeb8122.jpg



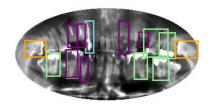
Cavity Implant Fillings

Impacted Tooth

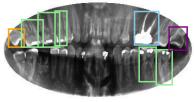
Image: 0170\_jpg.rf.4fd8f8e6179d4c147396b5dfa63fb65e.jpg



lmage: 0639\_jpg.rf.15e60af9d988588d7d28aa63a90722fa.jpg



Fillings Impacted Tooth Implant Cavity



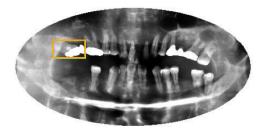
Implant
Impacted Tooth
Fillings
Cavity

#### Pair Frequencies:

```
['Fillings', 'Impacted Tooth']: 11 image(s)
['Cavity', 'Fillings']: 26 image(s)
['Cavity', 'Implant']: 5 image(s)
```

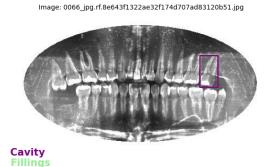
#### Grouped Bounding Boxes with Multiple Classes

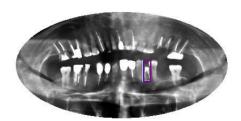
Image: 0013\_jpg.rf.18d48fad3e2d024f79264bc1a060bef0.jpg



Fillings Impacted Tooth

Image: 0308\_jpg.rf.39bfefbd46345a3821ecb4c7a60ec85d.jpg





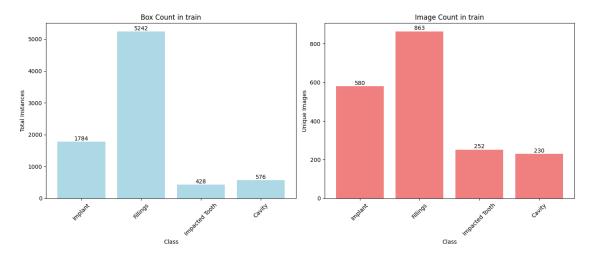
Cavity Implant

42 boxes with mutiple label.

```
# Step 3: Plot class distribution
fixed_class_order = ["Implant", "Fillings", "Impacted Tooth", "Cavity"]
plot_class_distribution(class_counts, fixed_class_order)
```

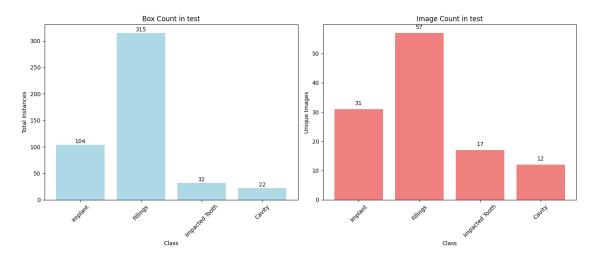
Folder: train

Total box count per class: [1784, 5242, 428, 576] Image count per class : [580, 863, 252, 230]

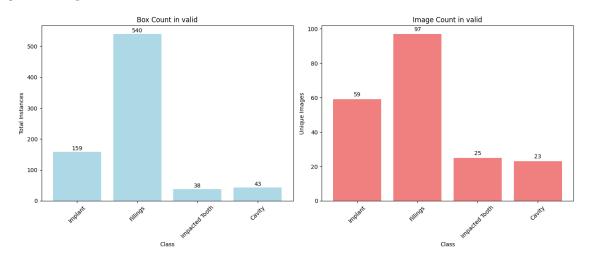


Folder: test

Total box count per class: [104, 315, 32, 22]
Image count per class : [31, 57, 17, 12]



Folder: valid
Total box count per class: [159, 540, 38, 43]
Image count per class : [59, 97, 25, 23]



## 1.5 SegFormer for Teeth Segmentation

In this section, we use a pretrained **SegFormer-B0** model fine-tuned on dental imagery for **semantic segmentation of teeth**.

The model used is:

AutoModelForSemanticSegmentation.from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassaru/segformer-b0-finetuned-teeth-segformer-b0-finetuned-teeth-segmentation).from\_pretrained("vimassa

We apply it to X-ray images to segment regions containing teeth. This step is helpful for preprocessing, analysis, and focusing attention on relevant anatomical structures. The predictions are visualized as segmentation masks using a colormap.

Model source: vimassaru/segformer-b0-finetuned-teeth-segmentation

Code: See attached file segmentation\_utils.py

```
[8]: from segmentation_utils import batch_infer_and_save
from pathlib import Path

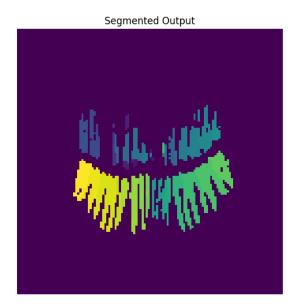
batch_infer_and_save(
    source_folder = "./assets/source_img",
    output_folder = "./assets/segformer_outputs",
    pattern="*.jpg",
    max_images = 3
)
```

/Users/hananalaskar/miniforge3/envs/yolov11\_env/lib/python3.11/site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See

https://ipywidgets.readthedocs.io/en/stable/user\_install.html from .autonotebook import tqdm as notebook\_tqdm

 ${\tt Processing:~0001\_jpg.rf.30a42966fb9c51553f6949b70234218d.jpg}$ 

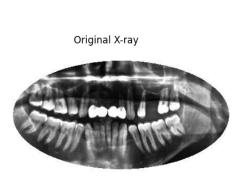


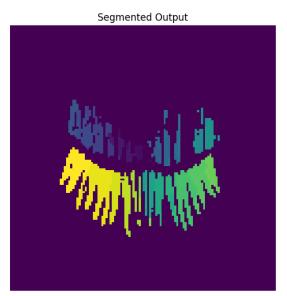


Saved: assets/segformer\_outputs/0001\_jpg.rf.30a42966fb9c51553f6949b70234218d\_s

egformer\_result.png

 ${\tt Processing:~0001\_jpg.rf.57229a11e925669019e179341e22c97a.jpg}$ 

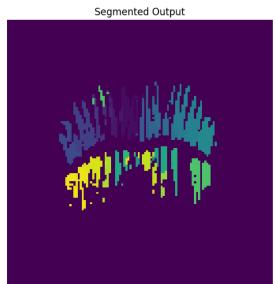




Saved: assets/segformer\_outputs/0001\_jpg.rf.57229a11e925669019e179341e22c97a\_s egformer\_result.png

Processing: 0001\_jpg.rf.f94abcb7858bb419a7202ef60ef95bd6.jpg





Saved: assets/segformer\_outputs/0001\_jpg.rf.f94abcb7858bb419a7202ef60ef95bd6\_s egformer\_result.png

## 1.6 Feature Analysis of X-rays and Segmentation Masks

In this section, we perform feature-based analysis of **dental X-ray images** and their **segmentation masks** using color histograms.

## 1.6.1 Key Steps

- 1. Feature Extraction: We compute normalized RGB histograms for each image and mask.
- 2. **Dimensionality Reduction**: Project histogram features using **PCA**, **t-SNE**, and **UMAP** to visualize and compare image-level variability.
- 3. Visualization: Identify and plot image extremes (Min, Mid, Max) across embedding axes.
- 4. Ratio Metrics: Calculate and visualize:
  - Missing Teeth Ratio (portion of image area not covered by teeth in the mask)
  - Darkness Ratio (portion of low-intensity pixels in the image)
- 5. **Joint Analysis**: Generate a 2D histogram to explore the correlation between the two ratios.

### Code Source: mask\_feature\_analysis.py

This analysis provides insight into the variability and visual characteristics of the dataset, helping inform preprocessing and model design decisions.

[1]: from mask\_feature\_analysis import \*

```
/Users/hananalaskar/miniforge3/envs/yolov11_env/lib/python3.11/site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html from .autonotebook import tqdm as notebook_tqdm
```

Found 1269 source images and 1269 mask images.

/Users/hananalaskar/miniforge3/envs/yolov11\_env/lib/python3.11/site-packages/umap/umap\_.py:1952: UserWarning: n\_jobs value 1 overridden to 1 by setting random\_state. Use no seed for parallelism.
warn(
OMP: Info #276: omp\_set\_nested routine deprecated, please use

OMP: Info #2/6: omp\_set\_nested routine deprecated, please use omp\_set\_max\_active\_levels instead.

CSVs saved to /Volumes/L/L\_PHAS0077/yolo/explore\_data/analysis\_outputs

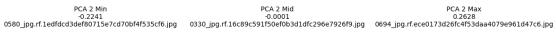
Original: PCA 1: Min vs. Mid vs. Max

PCA 1 Min PCA 1 Mid PCA 1 Mid O.3021
-0.2841
0938 jpg.rf.476b1ea283c5ccbbddaa023eb40a46d8.jpg 0194 jpg.rf.3fa08ba5eb780e87abe9054d5c262513.jpg 0158\_jpg.rf.6ba9ac13623e5a1dd9ca15ec2dc6a4a5.jpg

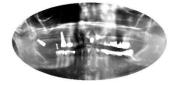














Original: PCA 3: Min vs. Mid vs. Max

PCA 3 Min PCA 3 Mid PCA 3 Max 0.1793 0.0000 0.2680
0710\_jpg.rf.lec82f15d2399e9df2252f4908e44b03.jpg 0009\_jpg.rf.957a0a16c5101765b0679e95eb9619a3.jpg 0158\_jpg.rf.6ba9ac13623e5a1dd9ca15ec2dc6a4a5.jpg



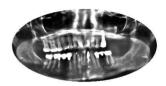




Original: tSNE 1: Min vs. Mid vs. Max

tSNE 1 Min tSNE 1 Mid tSNE 1 Max
-18.2765 -0.0184 19.1016
0719\_jpg.rf.041f488043af405b5b8431efc3d8f157.jpg 0323\_jpg.rf.2bd124050fdcb8c212a28a98519b6f5c.jpg 0312\_jpg.rf.a3b1695f851900ec415a5f75cb8283a2.jpg







Original: tSNE 2: Min vs. Mid vs. Max

 tSNE 2 Min
 tSNE 2 Mid
 tSNE 2 Max

 -13.2048
 0.0508
 13.6213

 0216\_jpg.rf.383ad8db30c3550784f4224029ac85b0.jpg
 0926\_jpg.rf.a2e580fab789e0b19d1cdcf2348484cc.jpg
 0710\_jpg.rf.lec82f15d2399e9df2252f4908e44b03.jpg







tSNE 3 Min tSNE 3 Mid tSNE 3 Max
-8.5056 0.1867 7.8576
0764\_jpg.rf.b8fffd780e5a12b7ec1fa76401e58b16.jpg 0401\_jpg.rf.4ee77b28f8a16c155427c0843370684c.jpg 0528\_jpg.rf.e77c08c50a3a5fa6775a204568db14fe.jpg





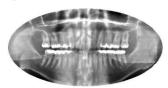


Original: UMAP 1: Min vs. Mid vs. Max

UMAP 1 Min UMAP 1 Mid UMAP 1 Max
-1.5263 7.1693 13.0275
0158\_jpg.rf.acfc32660c641086b7fa9a7f37d9130c.jpg 0054\_jpg.rf.b81c1de4282e2881bc92f9d5b6ca106f.jpg 0812\_jpg.rf.ea6f0c99e94cc51c5a17d6b32e05221a.jpg







Original: UMAP 2: Min vs. Mid vs. Max

UMAP 2 Min UMAP 2 Mid UMAP 2 Max 2.1455 2.6386 7.5325 0641\_jpg.rf.b40d29cb838c0bbe0bcf079f35ede7ce.jpg 0368\_jpg.rf.ae4c80bc75e51300b4de70922bf5e637.jpg 0174\_jpg.rf.ee4210bb5799f6fb0f645af4e46d1a84.jpg







Original: UMAP 3: Min vs. Mid vs. Max

UMAP 3 Min 0.7836 UMAP 3 Mid 0.7836 0.7836 0.763\_jpg.rf.9da3a40d8bb82c6077def7e3dc310a0b.jpg 0926\_jpg.rf.a2e580fab789e0b19d1cdcf2348484cc.jpg 0914\_jpg.rf.f6f25052c3571ed02ac9c0088dd8c338.jpg



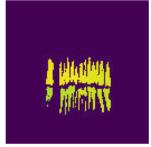


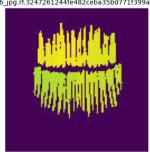


[4]: visualize\_extremes(df\_masks, ["PCA 1", "PCA 2", "PCA 3"], title\_prefix="Mask: ")





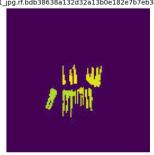


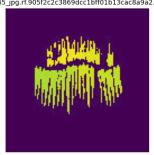


Mask: PCA 2: Min vs. Mid vs. Max

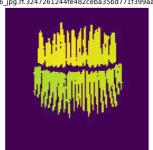
PCA 2 Min PCA 2 Mid PCA 2 Mid PCA 2 Max
-0.0164 0.0000 0825\_jpg.rf.a36d73e17d7a1da6435245915ea9f14f,jpg 0931\_jpg.rf.bdb38638a132d32a13b0e182e7b7eb30.jpg 0845\_jpg.rf.905f2c2c3869dcc1bff01b13cac8a9a2.jpg



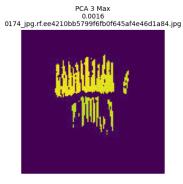




Mask: PCA 3: Min vs. Mid vs. Max 







visualize\_combined\_pca(df\_combined)

PCA 1 orig Min -0.2841 — 0938\_jpg.rf.476b1ea283c5ccbbddaa023eb40a46d8.jpg



PCA 1 orig Mid 0.0005 — 0194\_jpg.rf.3fa08ba5eb780e87abe9054d5c262513.jpg



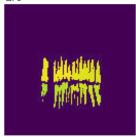
PCA 1 orig Max 0.3929 — 0158\_jpg.rf.6ba9ac13623e5a1dd9ca15ec2dc6a4a5.jpg



PCA 1 mask Min -0.0813 — 0320\_jpg.rf.01af7923754c344871281322fb8e5d66.jpg



PCA 1 mask Mid -0.0000 — 0304\_jpg.rf.4d4e47e46979e47028a60557236ba1cc.jpg



PCA 1 mask Max 0.1602 — 0006\_jpg.rf.3247261244fe482ceba35bd771f399aa.jpg

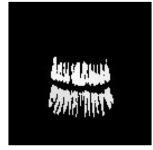


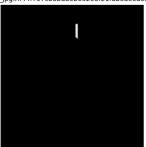
## visualize\_ratios(df\_combined)

Segmentation Mask: Missing Teeth Ratio (Norm) Extremes

Segmentation Mask Min
Missing Teeth Ratio (Norm): 0.00
Missing Teeth Ratio (Norm): 0.53
Missing Teeth Ratio (Norm): 0.53
Missing Teeth Ratio (Norm): 0.00
0217\_jpg.rf.b21d198dfc0ce564889cbf2a2912f98d.jpg
0318\_jpg.rf.56f8ed8a60455d6ff34ec81e762789a1.jpg
0320\_jpg.rf.44f757cb8bda6b63208f21fab5ae6a5d.jpg







## Original X-Ray: Darkness Ratio (Norm) Extremes

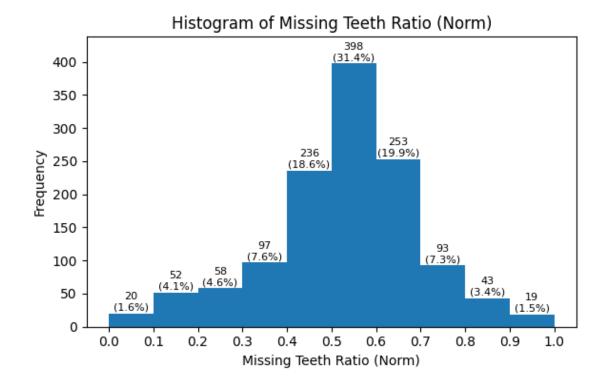
Original X-Ray Min
Darkness Ratio (Norm): 0.00
Darkness Ratio (Norm): 0.00
Darkness Ratio (Norm): 0.27
Darkness Ratio (Norm): 0.00
0051\_jpg.rf.8488c6bfe540f9a79ae7d490e2fab827.jpg
0402\_jpg.rf.63994d789ad1787836039de7b5b14860.jpg
0158\_jpg.rf.6ba9ac13623e5aldd9ca15ec2dc6a4a5.jpg



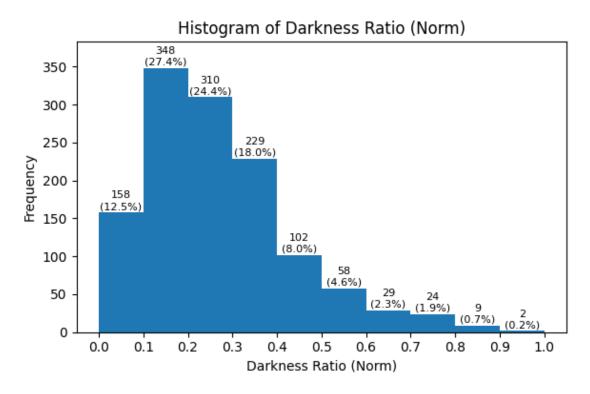




save\_ratio\_histograms(df\_combined, output\_dir="/Volumes/L/L\_PHAS0077/ ⇔analysis\_outputs")



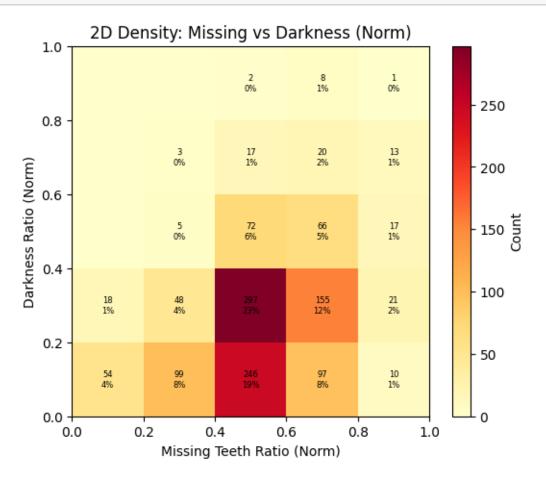
Saved histogram for Missing Teeth Ratio (Norm) at /Volumes/L/L\_PHASO077/analysis\_outputs/missing\_teeth\_ratio\_hist.png



Saved histogram for Darkness Ratio (Norm) at /Volumes/L/L\_PHAS0077/analysis\_outputs/darkness\_ratio\_hist.png

[8]: save\_joint\_ratio\_heatmap(df\_combined, output\_dir="/Volumes/L/L\_PHAS0077/

analysis\_outputs")



Saved joint-ratio heatmap at /Volumes/L/L\_PHASO077/analysis\_outputs/missing\_vs\_darkness\_heatmap.png

[]: