Identification of Unhealthy Teeth Using Convolutional Neural Networks on the Tufts Dental Dataset

Shawn Hwang

Mentor: Jericho Lawson | Department of Statistics at the University of California, Riverside | Data Science B.S. | shawnhwang1@gmail.com

Abstract

Dental caries are one of the most common issues seen in dentistry and are often diagnosed through expert analysis of panoramic dental X-rays. This research explores the use of deep learning to automate the identification of unhealthy teeth from panoramic x-rays, through the Tufts panoramic X-ray dental dataset [1]. Individual teeth are extracted from full mouth X-rays using their respective annotated bounding boxes, and each tooth is labeled as healthy or carious based on expert reports. Several convolutional neural network (CNN) models, including ResNet-50, DenseNet-121, and EfficientNet-B0, are used to classify tooth images. To improve model transparency, we will also use Grad-CAM to visualize which parts of the image influenced the model's predictions. The goal of this project is to develop a reliable and explainable tool that can supplement dentists' clinical judgment and assist in early, consistent identification of dental caries.

Background

Dental caries, commonly known as **cavities**, are among the most prevalent chronic diseases globally, impacting individuals of all ages. Detecting caries early is essential for preventing more serious oral health issues. Traditionally, dentists interpret dental X-rays manually, a process that can be subjective and labor-intensive. With the rapid expansion of big data and artificial intelligence, **image processing** has become a key tool in healthcare and diagnostics. In medical imaging, it has become a tool that allows for analysis of image data.

This project explores image processing and recognition through neural networks in the context of dentistry. The goal is to investigate how machine learning models can be trained to analyze dental X-rays and classify individual teeth as either healthy or carious. This kind of automated recognition system has the potential to assist dental professionals by supplementing their clinical decisions with fast, explainable predictions.

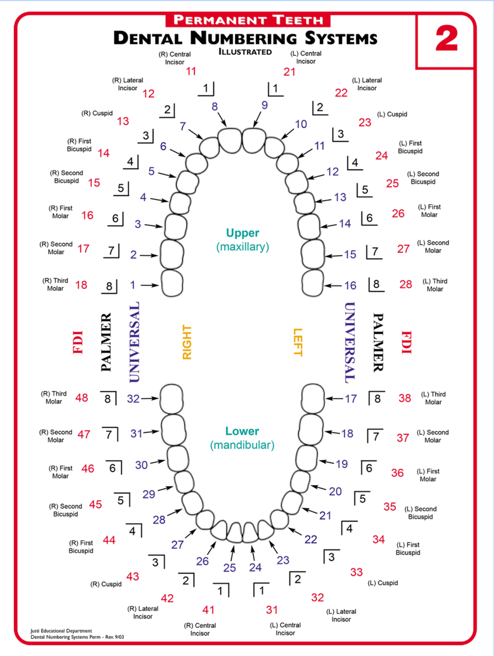

Figure 1: Teeth Numbering System

The study uses the ***Tufts Dental Database***, a large-scale collection of panoramic X-ray images paired with expert-labeled annotations. This dataset enables the training and evaluation of deep **convolutional neural networks** (CNNs), including ResNet50, DenseNet121, and EfficientNetB0, for dental classification tasks [1].

Grad-CAM visualizations are also employed to interpret the predictions and identify which parts of the image the models rely on most. This was done to show more **transparency** and demonstrate how the model is making its predictions.

By applying neural networks to dental X-ray segmentation and classification, this project demonstrates a real-world application of image recognition technology, which demonstrates how advances in these methods can enhance systems not only in dentistry, but also in broader fields like medicine and forensic analysis.

Figure 2: Example of Mouth Image from Tufts Dental Dataset

Methods

This project uses a structured pipeline to classify individual teeth as carious or healthy based on panoramic dental X-rays from the Tufts Dental Dataset. The pipeline consists of four major stages: **isolation**, **labeling**, **CNN classification**, and **explainability** using Grad-CAM.

Isolation

- Individual teeth were cropped from the panoramic X-ray images using pre-annotated bounding boxes in the TUFTS Dental Database.
- The cropped images (e.g. tooth_19.jpg) allow the CNNs to focus on isolated teeth instead of entire panoramic images, reducing noise and increasing model precision.

Labeling

- Labels were derived from expert annotations stored in expert.json, written by dental professionals at Tufts.
- If a description contained "within normal limits", all visible teeth were labeled as healthy. Otherwise, any tooth numbers (1–32) mentioned are marked as carious.

Figure 3: Labeling of Teeth

Figure 4: Specific Image of Tooth

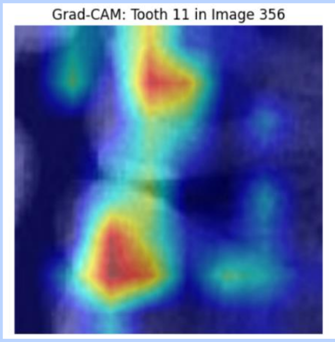

Figure 5: Using GradCAM on Tooth

Classification

These models were trained **with 5-fold cross-validation** on 1,884 labeled tooth images. Class weights were used to help with the large class imbalance during training.

- **ResNet50:** Uses skip connections to prevent vanishing gradients in deep networks. [3]
- **DenseNet121**: Connects layer-to-layer, improving gradient flow and reducing overfitting [4]
- **EfficientNetB0**: Uses compound scaling of depth, width, and resolution to provide high performance with fewer parameters. [5]

Explainability

Grad-CAM was used to generate heatmaps visualizing which parts of a tooth image influenced the CNN's classification to improve transparency.

- Red/yellow areas indicate regions that had the most influence on the model predicting carious (unhealthy). Blue regions had little to no effect on the model's decision.

Results

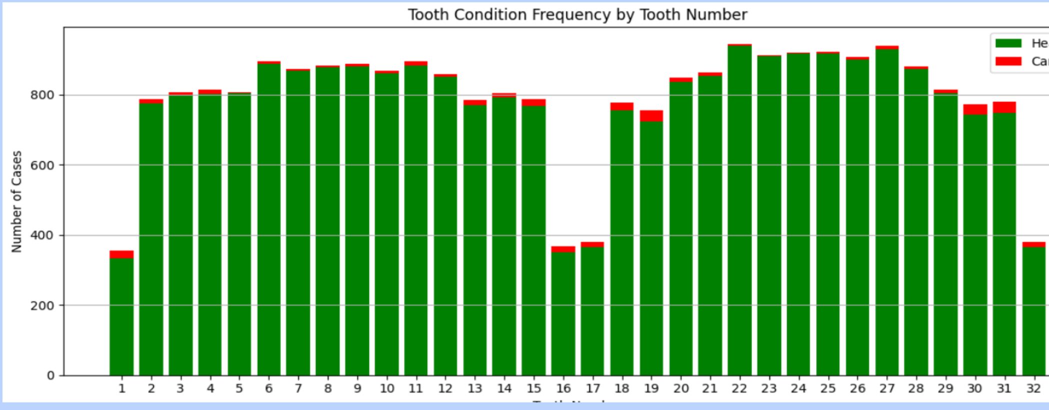

Figure 6: Tooth Condition Frequency by Tooth Number

Distribution of Labeled Teeth by Tooth # (in Figure 6)

- Shows class imbalance between healthy and carious teeth.
- Teeth 2-15 and 18-31 are more common in this dataset (800+ instances)
- Teeth 1, 16, 17, 32 are the least common possibly due to extractions (< 400 instances)

Heat Map of Carious Teeth (in Figure 7)

- Designed to reflect a real mouth: Top Row (1-16); Bottom Row (32-17)

Insights

- Tooth 1 has the highest proportion of caries at **6%**
- Molars/premolars such as #2–5, 12–15, 18–21, and 28–31 have caries proportions at **4%.** [6]
- Incisors and canines (#6–11 and #22–27) show a low proportion **under 1%,** which reflects dental trends [7]

Results (cont.)

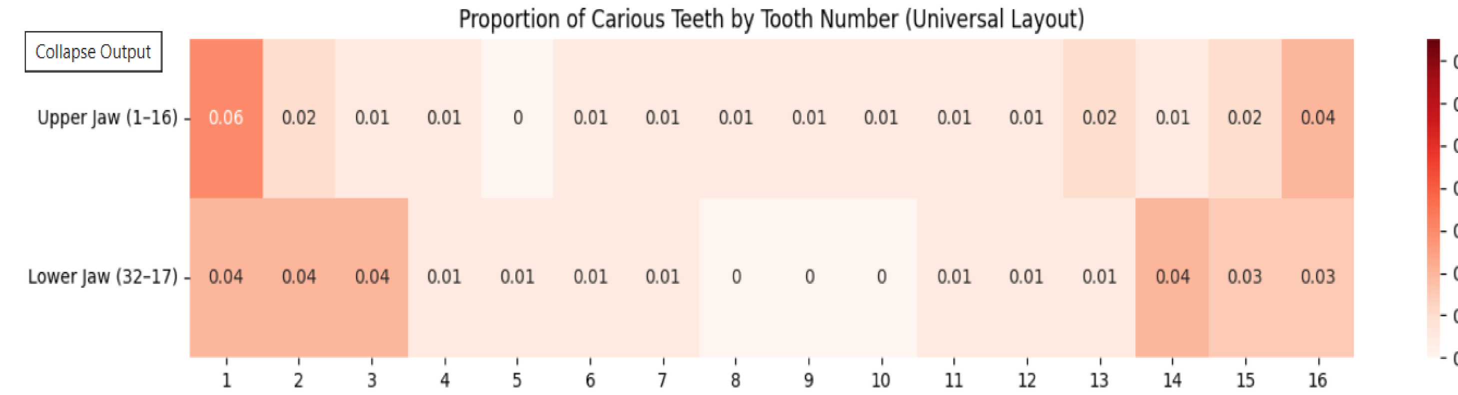

Figure 7: Proportion of Carious Teeth by Tooth Number (Universal Layout)

Model Information

- All images were resized to 256x256
- Trained with epoch of 15 per fold
- Adam Optimizer (learning rate of 0.001)
- Loss function used weighted cross entropy
- Data Augmentation: flips, rotations, and brightness

Model	Accuracy	F1- Score	Sensitivity	Specificity
ResNet-50	**72.03%**	**0.47**	**0.60**	**0.75**
DenseNet121	69.8%	0.43	0.57	0.73
EfficientNetB0	65.07%	0.43	0.65	0.65

Table 1: Accuracy Metrics Using Three Different Models

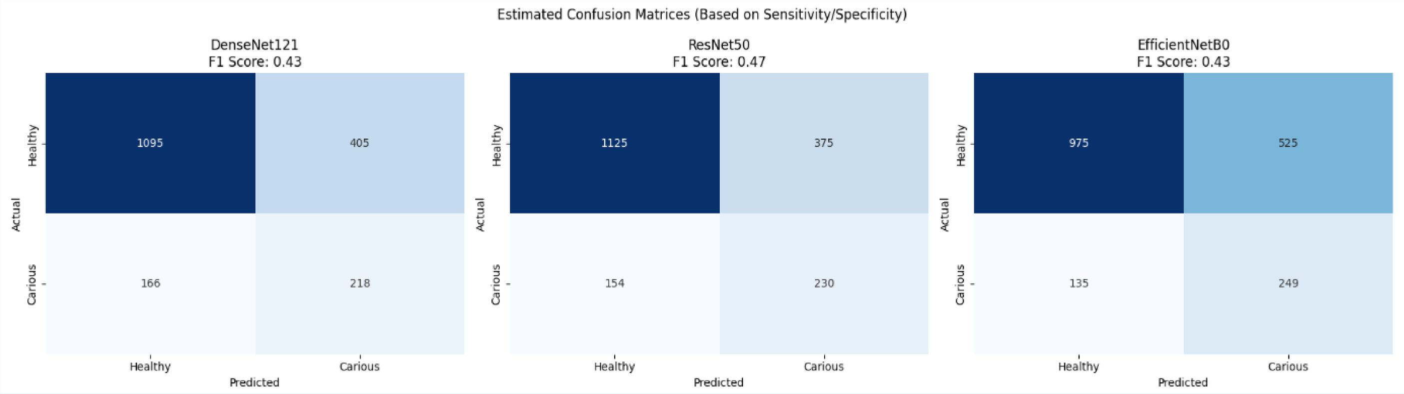

Figure 8: Confusion Matrices of Three Different Models

Conclusions

What We Did

- Extracted and labeled individual teeth from Tufts panoramic X-rays. Trained 3 CNNs (ResNet50, DenseNet121, EfficientNetB0) to classify teeth as healthy or carious. Evaluated model accuracy, F1 score, sensitivity, and specificity using 5-fold cross-validation. Used Grad-CAM to visualize which tooth areas influenced the model's decision.

Disadvantages

- The dataset had class imbalance (fewer carious teeth), which made it harder for models to learn minority class features.

Future Work/Improvements

- Increase size of dataset to have more carious teeth.
- Experiment with other CNN models to improve classification accuracy.
- Additional hyperparameter tuning to optimize models.

Acknowledgements & References

- Thank you to the SMART program for allowing me to participate in this research project. I would also like to say a special thanks to Jericho Lawson for his guidance, mentorship, and support throughout the research project.

[1] Panetta, K., Rajendran, R., Ramesh, A., Rao, S. P., & Agaian, S. (2021). *Tufts Dental Database: A Multimodal Panoramic X-ray Dataset for Benchmarking Diagnostic Systems*. IEEE Journal of Biomedical and Health Informatics. Website: http://tdd.ece.tufts.edu/

[2] Teeth Numbering System, 123Dentist. *Understanding Dental Lingo*. https://www.123dentist.com/understanding-dental-lingo/

[3] He, K. et al. (2016). "Deep Residual Learning for Image Recognition." CVPR. https://ieeexplore.ieee.org/document/7780459

[4] Huang, G. et al. (2017). "Densely Connected Convolutional Networks." CVPR. https://ieeexplore.ieee.org/document/8099726

[5] Tan, M. & Le, Q. (2019). "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." ICML. https://proceedings.mlr.press/v97/tan19a.html

[6] National Institutes of Health (2010). Prevalence of caries on individual tooth surfaces and its correlation with caries experience. U.S. National Library of Medicine. https://pmc.ncbi.nlm.nih.gov/articles/PMC2897860/

[7] Broadbent, J.M., et al. (2013). Permanent dentition caries through the first half of life. British Dental Journal. https://pubmed.ncbi.nlm.nih.gov/24113990/