Dental Image Segmentation

Van Rossum

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Meet the Team

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All Role

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Modelling

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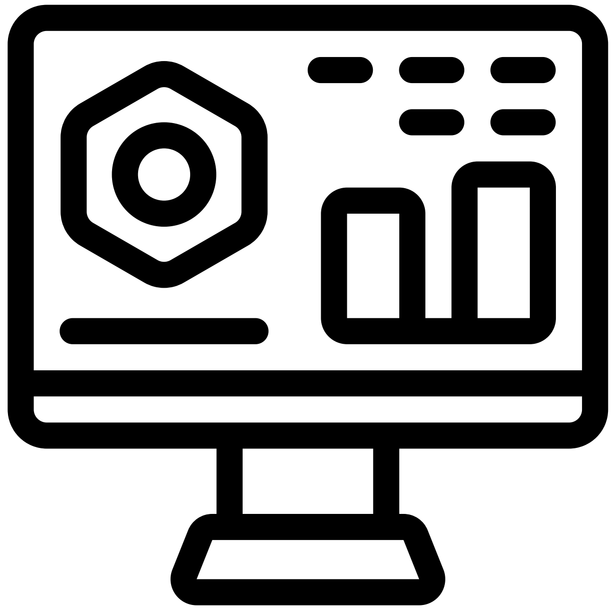
Background & Problem Statement

- The **application of Artificial Intelligence** in dental healthcare has a **very promising role** due to the **abundance of imagery and non-imagery-based clinical data**
- Expert analysis of dental radiographs can provide **crucial information** for **clinical diagnosis and treatment**
- **CNN** have **achieved** the highest **accuracy** in various benchmarks, including **analyzing dental X-ray images** to **improve clinical care quality**

Objectives & Scope

The primary goal is to **pinpoint the best-performing model** that **balances accuracy** and **computational efficiency**



This balance is **crucial for deploying these models on low- to medium-spec hardware, making advanced dental image analysis accessible** and **practical in various clinical settings.**

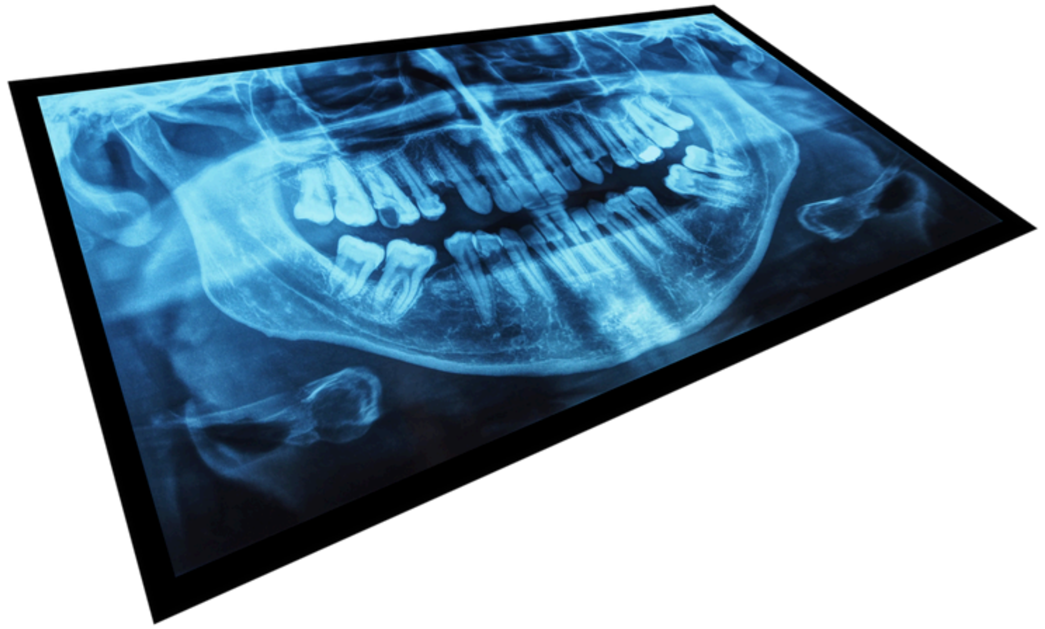
By **leveraging lightweight backbones,** we aim to **achieve high-quality segmentation without the need for high-end infrastructure,** thus **broadening the scope of these technologies' applicability.**

Data Collection

We used the

Tufts Dental Database

created by the Panetta Visualization, Sensing & Simulation Research Laboratory

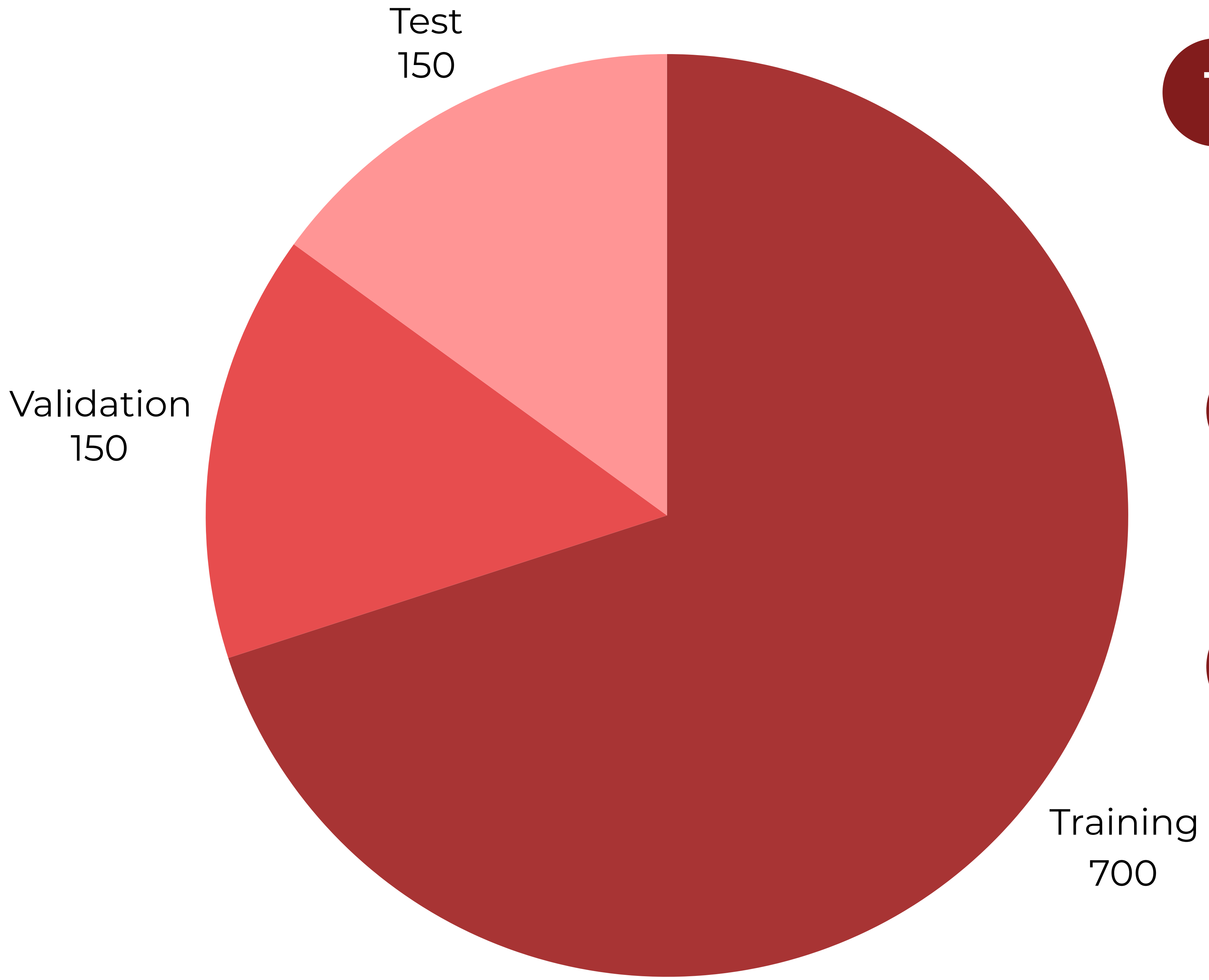


- **The Tufts Dental Database,** a new **X-ray panoramic radiography image dataset,** has been presented. This dataset **consists of 1000 panoramic dental radiography images** with expert labeling of abnormalities and teeth.

- **These images capture detailed structures including teeth, jawbones, and surrounding areas,** making them **essential for identifying issues** like **impacted teeth**, **jaw disorders,** and **assessing overall dental health.**

- **The dataset** is meticulously **annotated to support the development and evaluation of advanced segmentation models.**

Data Preparation



To **enhance** the **robustness** of our dataset, we **applied a variety** of **transformations** from Albumentations library.:

1.Geometric Transformations

- These include random rotations, translations, scaling, and keypoint transformations to simulate different viewpoints and image perspectives.

2.Color and Contrast Adjustments

- Adjustments to brightness, contrast, saturation, and hue for varying lighting, improve model's ability to generalize.

3.Blur and Noise

- Introduction of Gaussian blur, motion blur, and noise to make the model robust to different types of image.

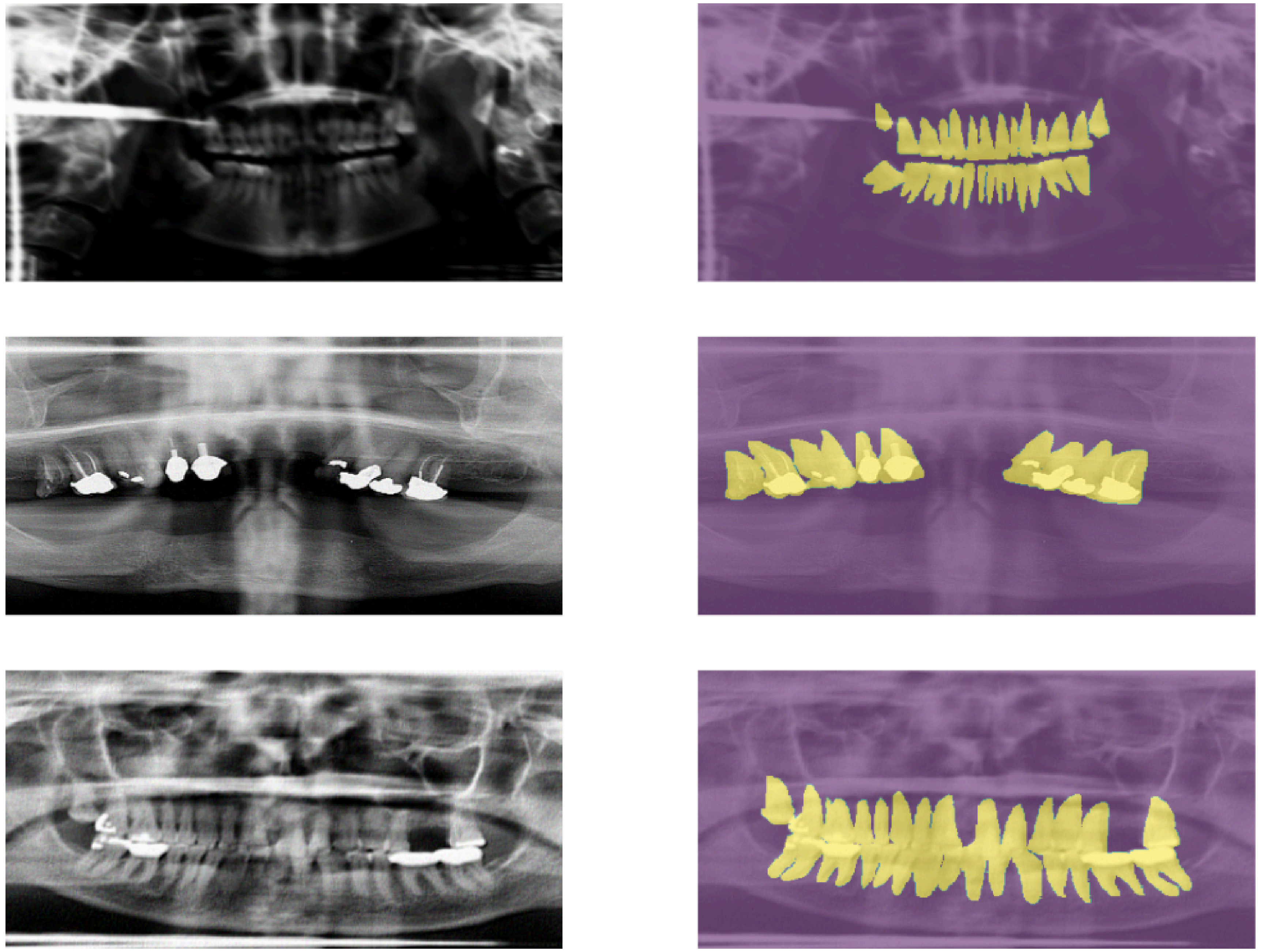
4.Distorsions & Flips

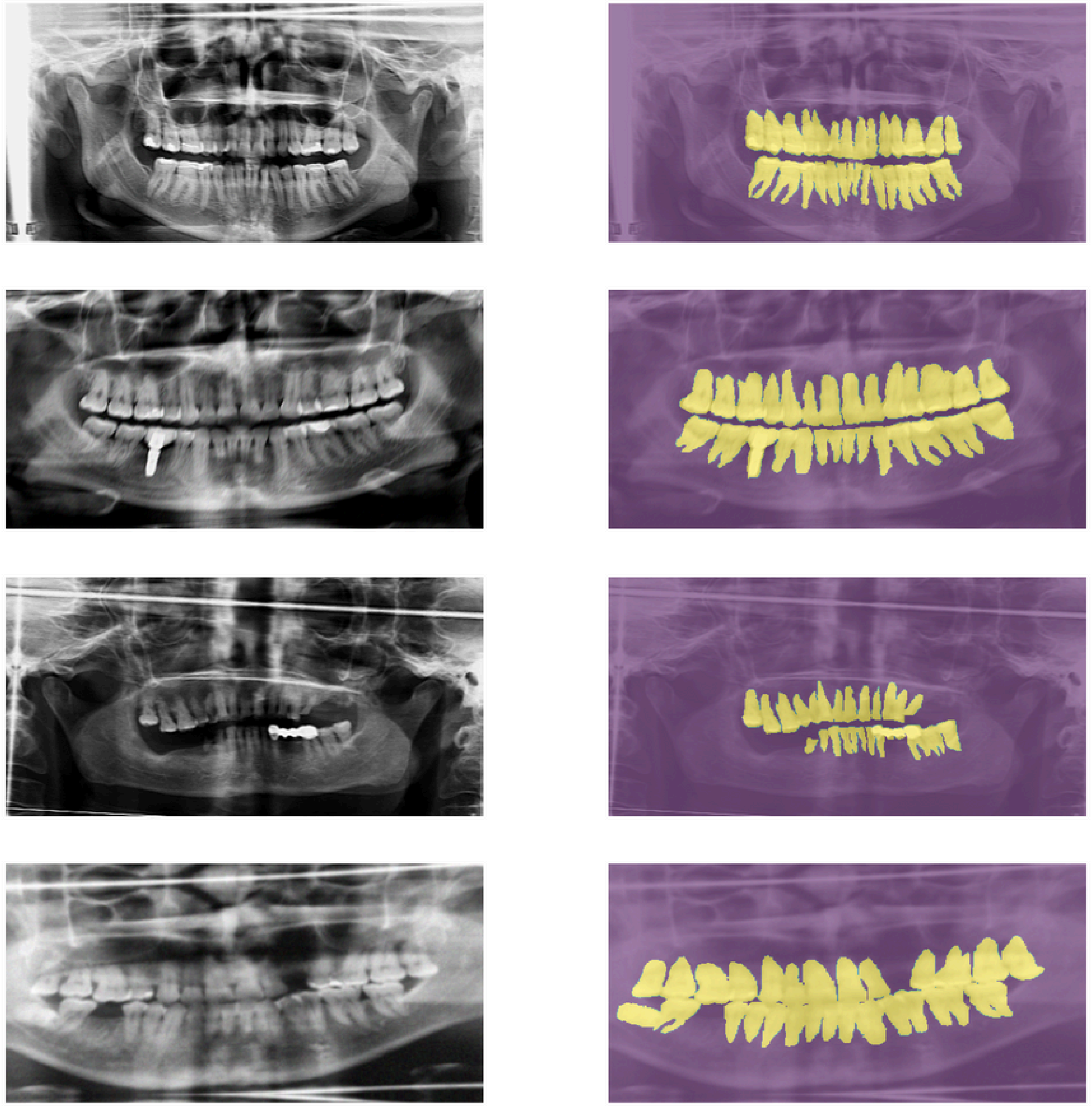
- Application of elastic transformations, grid distortions, and optical distortions and Horizontal flips to provide the model with a diverse set of orientations.

5.Other Effects

- Additional effects such as CLAHE (Contrast Limited Adaptive Histogram Equalization), sharpen, emboss, blur, and gamma correction.

Data Preparation



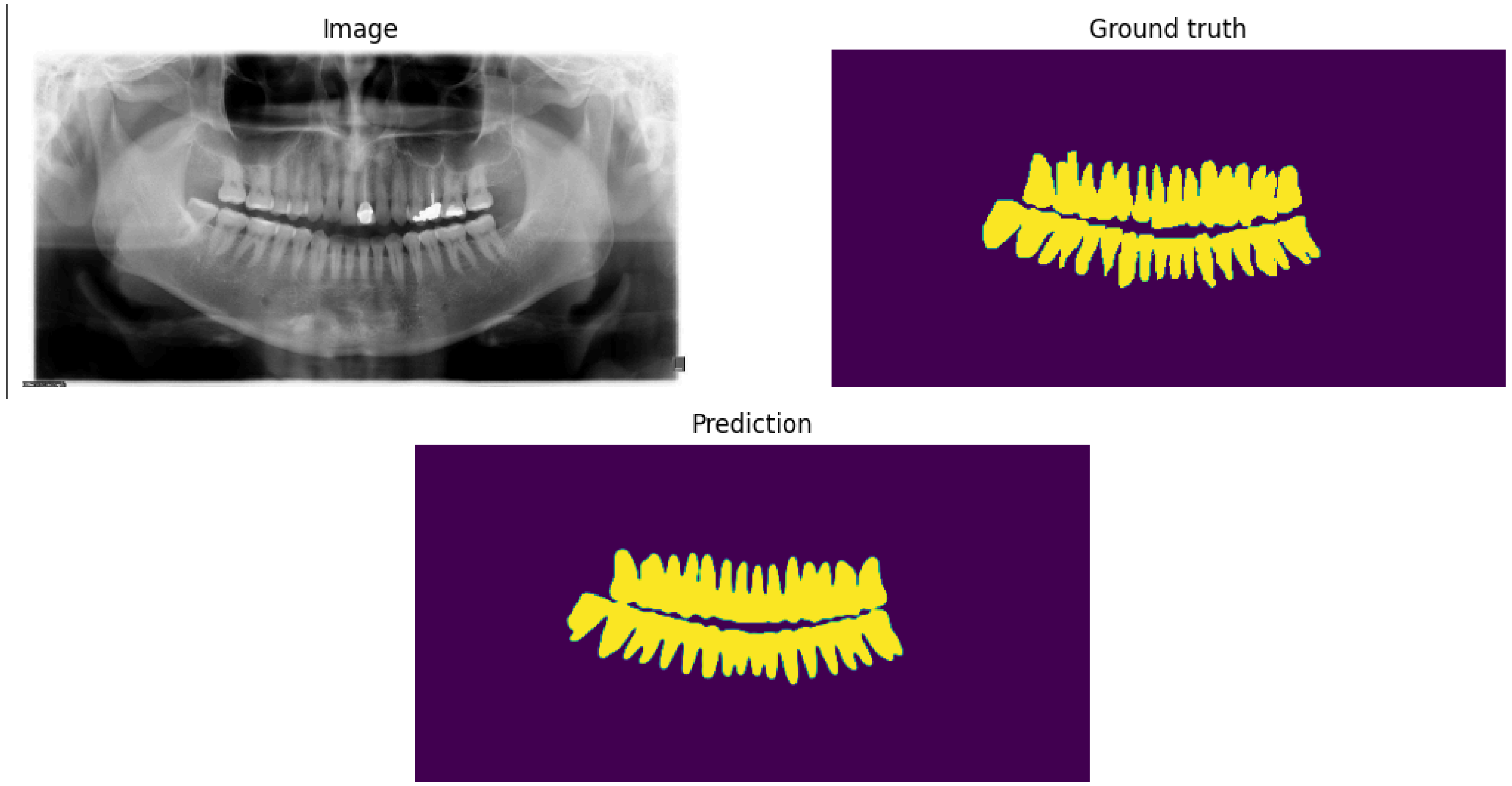


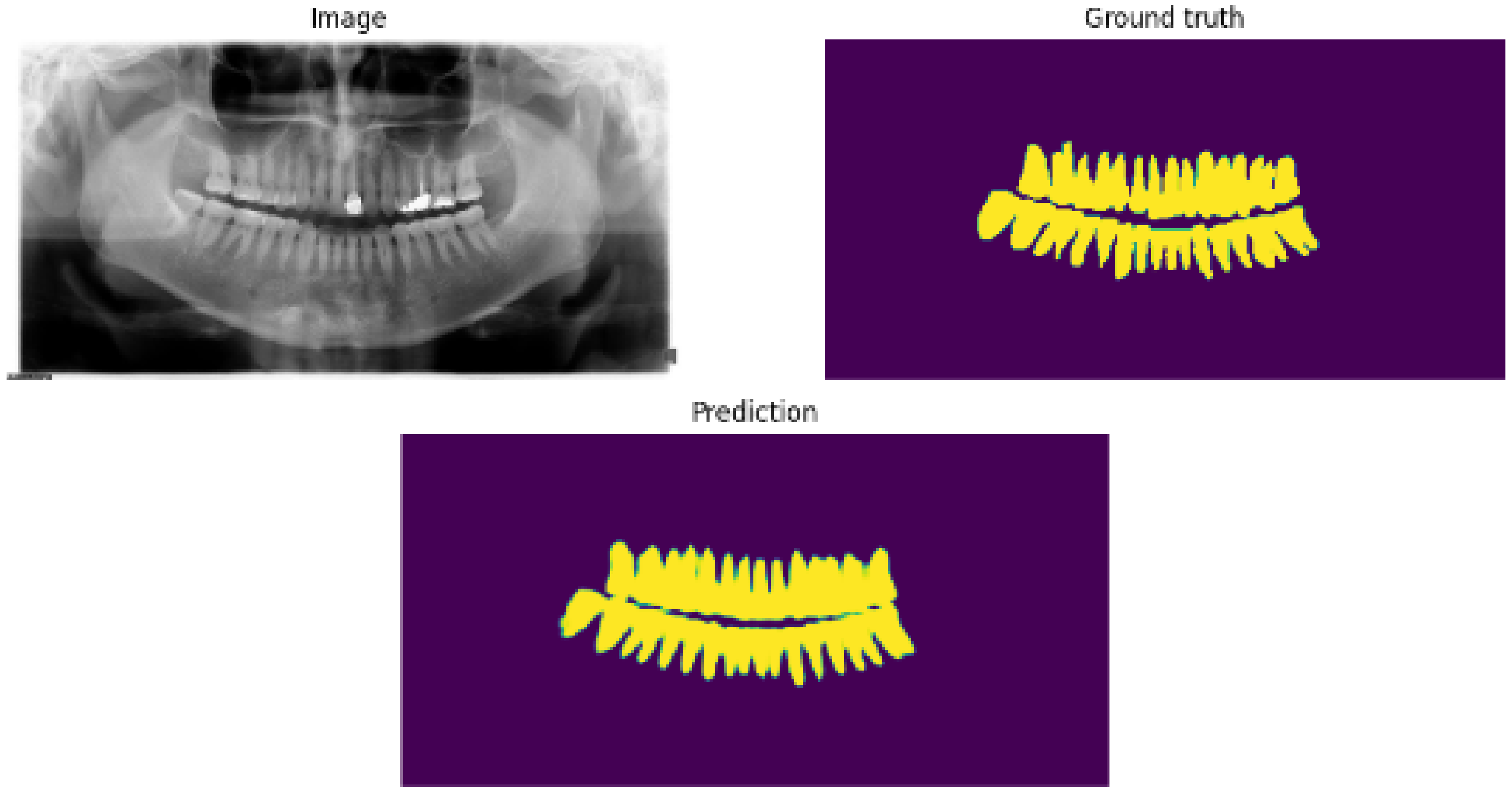
- These **augmentations** are carefully **applied to preserve the detailed information** within the images, **ensuring the augmented dataset remains a valuable resource** for **effective model training and testing.**

Model Development

The following segmentation architectures are implemented and compared:

• Unet	• PAN (Pyramid Attention Network)



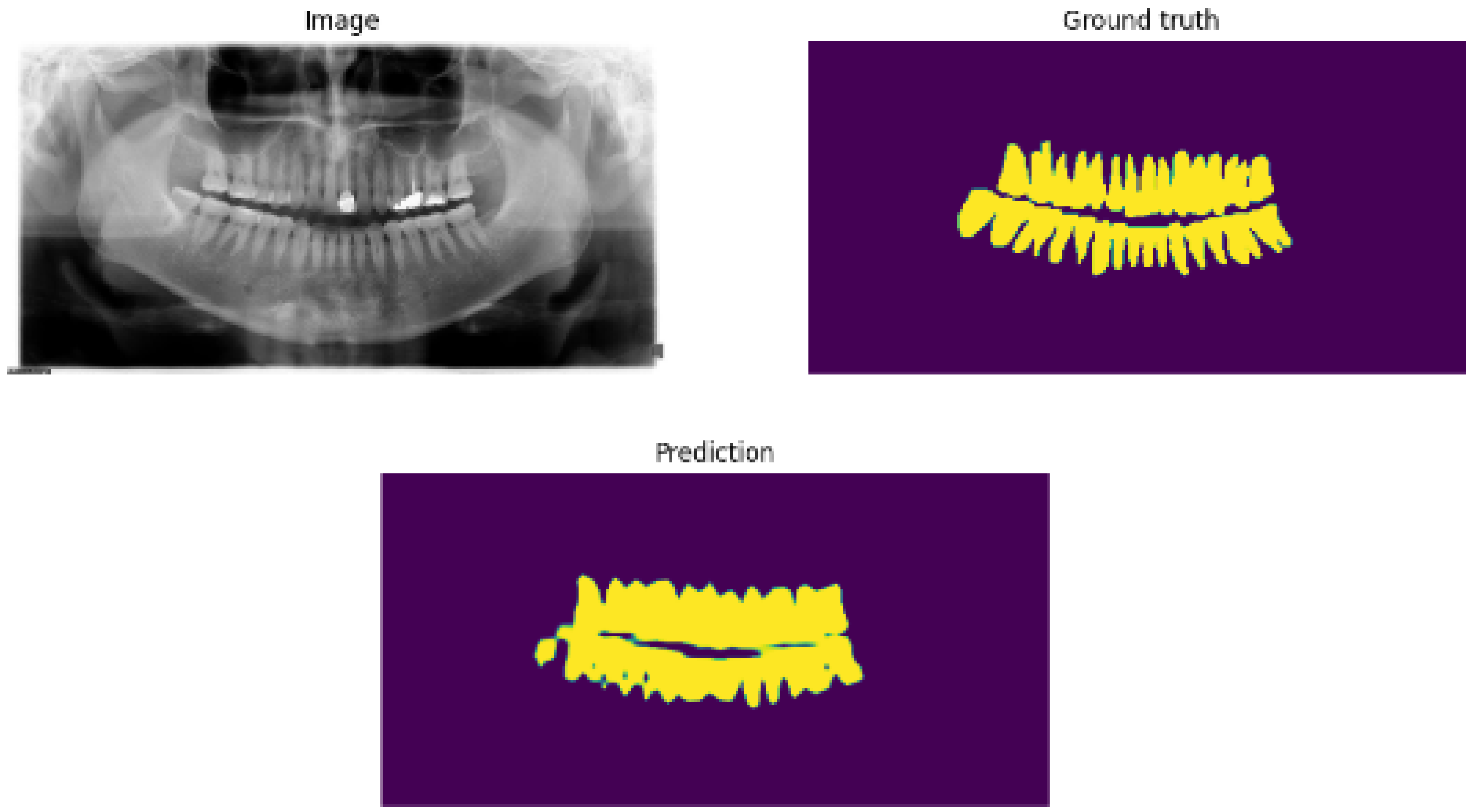


• MobileNet V2	• Resnet	• MobileNet V2	• Resnet

Model Development

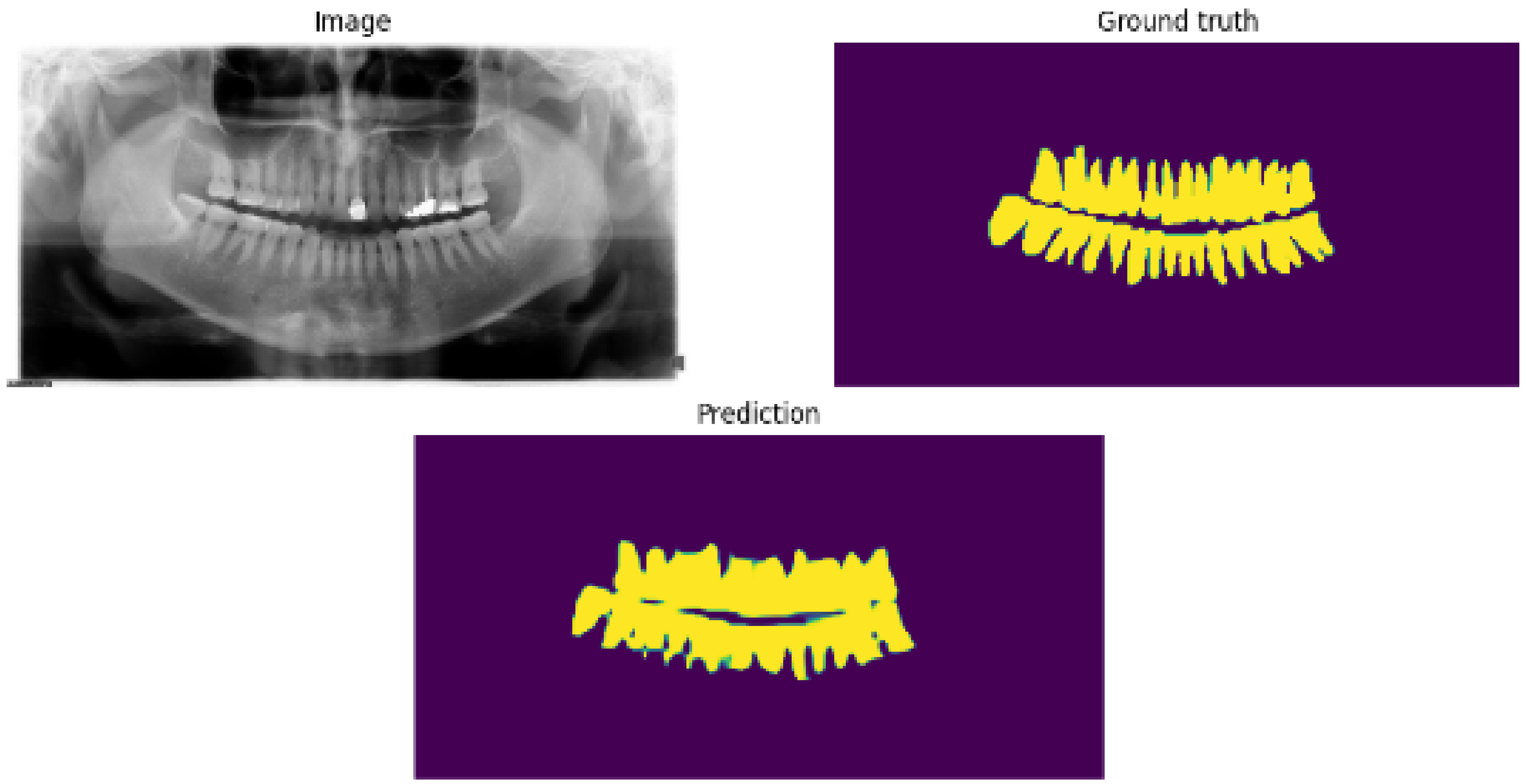
The following segmentation architectures are implemented and compared:

- **PSPNet (Pyramid Scene Parsing Network)**



- **MobileNet V2**
- **Resnet**

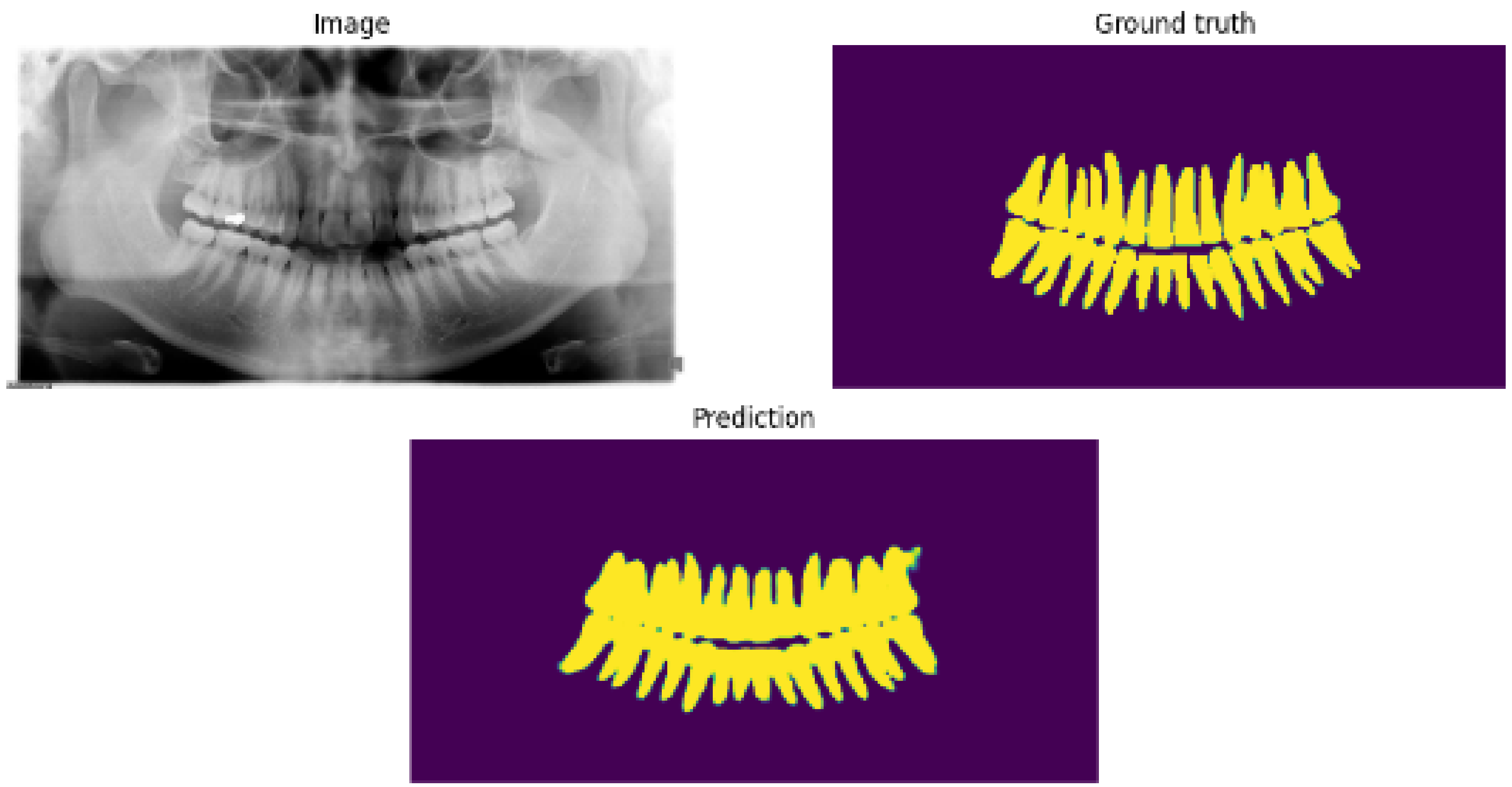
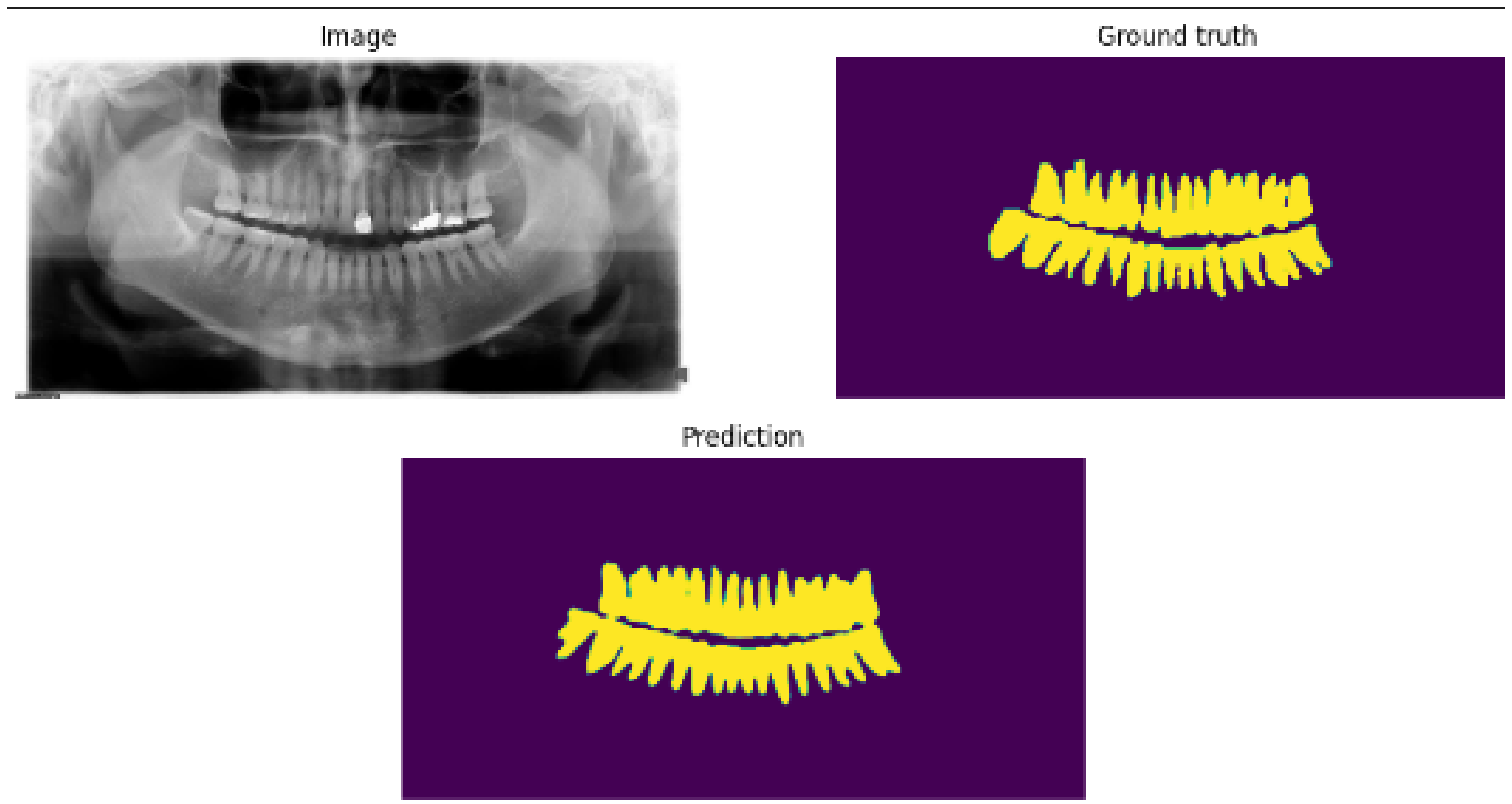
- **DeepLabV3**



- **MobileNet V2**
- **Resnet**

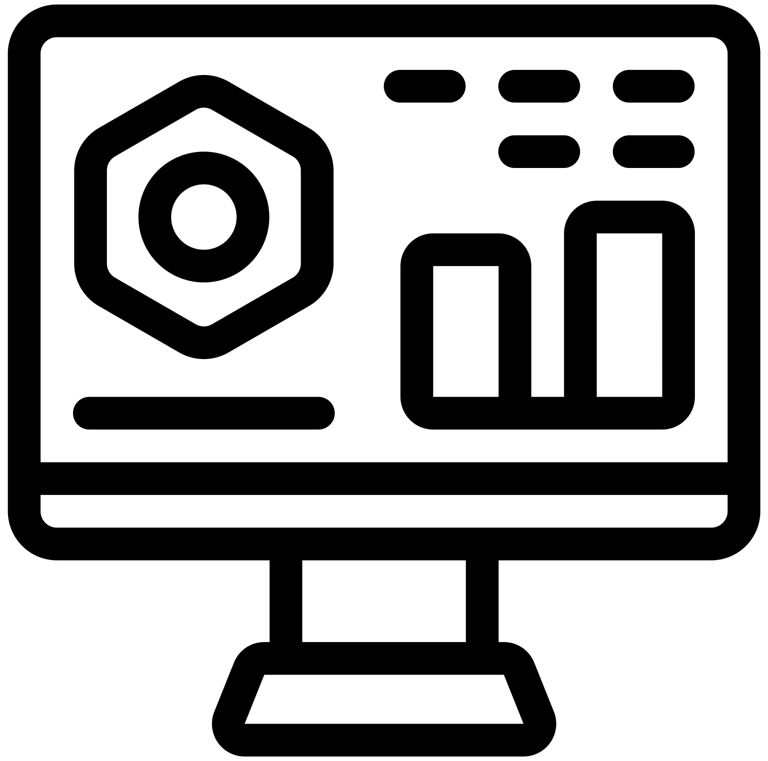
Model Development

The following segmentation architectures are implemented and compared:

• DeepLabV3+:	• U-Net++
	
• MobileNet V2 • Resnet	• MobileNet V2 • Resnet

Training & Optimization

The following hyperparameters are used for training the models:

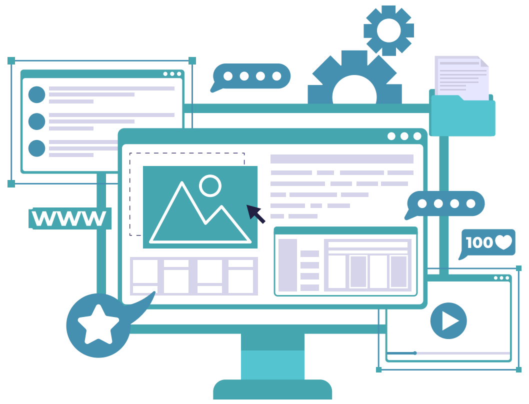


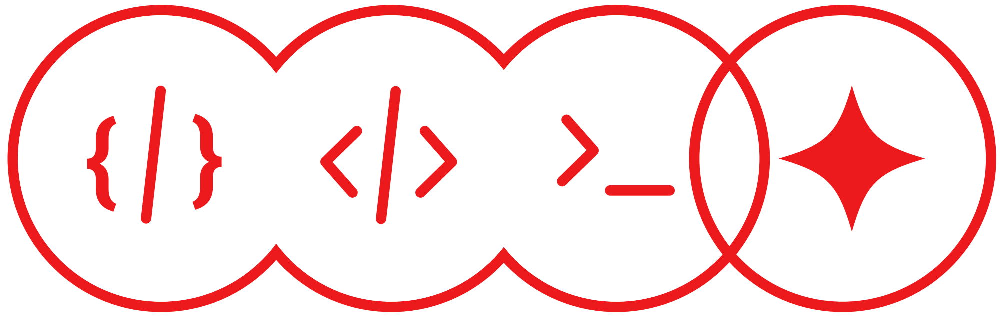
- Input Size: 256 x 512
- Batch Size: 32
- Optimizer: Adam
- Learning Rate: 1e-3
- Scheduler: Reduce On Plateau
    - Factor: 0.5
    - Patience: 5
- Early Stopping: Patience 20

Criterion and Evaluation Metrics

- We use DiceLoss as the loss function during training to improve the model's performance on segmentation tasks.
- The performance of each model is evaluated using the following metrics:

1. Dice Coefficient:
2. Pixel Accuracy:
3. IoU (Intersection over Union):





Results

- This table **summarizes the performance metrics** (Dice Coefficient, IoU, Pixel Accuracy, and Relative Time) on the **Validation set** for **various models with ResNet34 and MobilenetV2 backbones (with 300 epochs)**

Rank	Architecture	Encoder	Dice Coefficient	IoU Value	Pixel Accuracy	Average	Relative	Early Stopped
1	**U-Net++**	**ResNet34**	**0.9124**	**0.8401**	**0.9791**	**0.9105**	**55m 33s**	**89**
2	**U-Net**	**ResNet34**	**0.9078**	**0.8322**	**0.9778**	**0.9059**	**25m 0s**	**66**
3	**U-Net**	**MobilenetV2**	**0.9065**	**0.8296**	**0.9774**	**0.9045**	**31m 38s**	**81**
4	U-Net++	MobilenetV2	0.9045	0.8268	0.977	0.9028	35m 51s	87
5	DeepLabV3+	ResNet34	0.9056	0.8287	0.9773	0.9039	25m 26s	80
6	PAN	ResNet34	0.9056	0.8303	0.9776	0.9045	27m 15s	93
7	LinkNet	ResNet34	0.8306	0.9776	0.9069	0.9050	32m 42s	106
8	DeepLabV3+	MobilenetV2	0.898	0.8166	0.9756	0.8967	40m 18s	137
9	FPN	MobilenetV2	0.8951	0.812	0.9748	0.8939	35m 18s	120
10	PAN	MobilenetV2	0.8912	0.8069	0.9742	0.8908	31m 57s	111
11	DeepLabV3	ResNet34	0.8962	0.8134	0.9748	0.8948	44m 56s	84
12	DeepLabV3	MobilenetV2	0.8808	0.7884	0.9709	0.8800	43m 17s	77
13	PSPNet	ResNet34	0.89	0.8031	0.9732	0.8888	26m 37s	97
14	FPN	ResNet34	0.8877	0.8006	0.9731	0.8871	28m 30s	99
15	LinkNet	MobileNetV2	0.8157	0.9753	0.8977	0.8962	21m 23s	67
16	PSPNet	MobilenetV2	0.8797	0.7866	0.9706	0.8790	34m 46s	137

- The models are ranked based on the average of Dice Coefficient, IoU, and Pixel Accuracy.

Results

- This table **summarizes the performance metrics** (Dice Coefficient, IoU, Pixel Accuracy, and Relative Time) on **Test set** for **various models with ResNet34 and MobilenetV2 backbones.**

Test Set (Based on Average Score)

Rank	Architecture	Encoder	Test Dice	Test IoU	Test Accuracy	Average Score	Inference Time (s)
1	UNet	ResNet34	0.9048	0.8273	0.9778	0.9033	0.0111
2	FPN	MobileNetV2	0.8922	0.8074	0.9747	0.8914	0.0174
3	PSPNet	MobileNetV2	0.8760	0.7805	0.9705	0.8757	0.0182
4	PAN	MobileNetV2	0.8884	0.8026	0.9742	0.8884	0.0209
5	DeepLabV3+	MobileNetV2	0.8945	0.8111	0.9753	0.8936	0.0213
6	PSPNet	ResNet34	0.8866	0.7976	0.9730	0.8857	0.0213
7	DeepLabV3+	ResNet34	0.9028	0.8242	0.9773	0.9014	0.0224
8	LinkNet	MobileNetV2	0.8947	0.8112	0.9752	0.8937	0.0264
9	UNet++	ResNet34	0.9115	0.8387	0.9793	0.9098	0.0280
10	UNet++	MobileNetV2	0.9026	0.8236	0.9771	0.9011	0.0309
11	FPN	ResNet34	0.8835	0.7940	0.9728	0.8834	0.0379
12	LinkNet	ResNet34	0.9050	0.8275	0.9777	0.9034	0.0393
13	PAN	ResNet34	0.9031	0.8263	0.9775	0.9023	0.0656
14	DeepLabV3	ResNet34	0.8933	0.8088	0.9747	0.8923	0.0671
15	DeepLabV3	MobileNetV2	0.8768	0.7821	0.9705	0.8765	0.0564
16	UNet	MobileNetV2	0.9036	0.8247	0.9772	0.9018	0.0594

Test Set (Based on Inference)

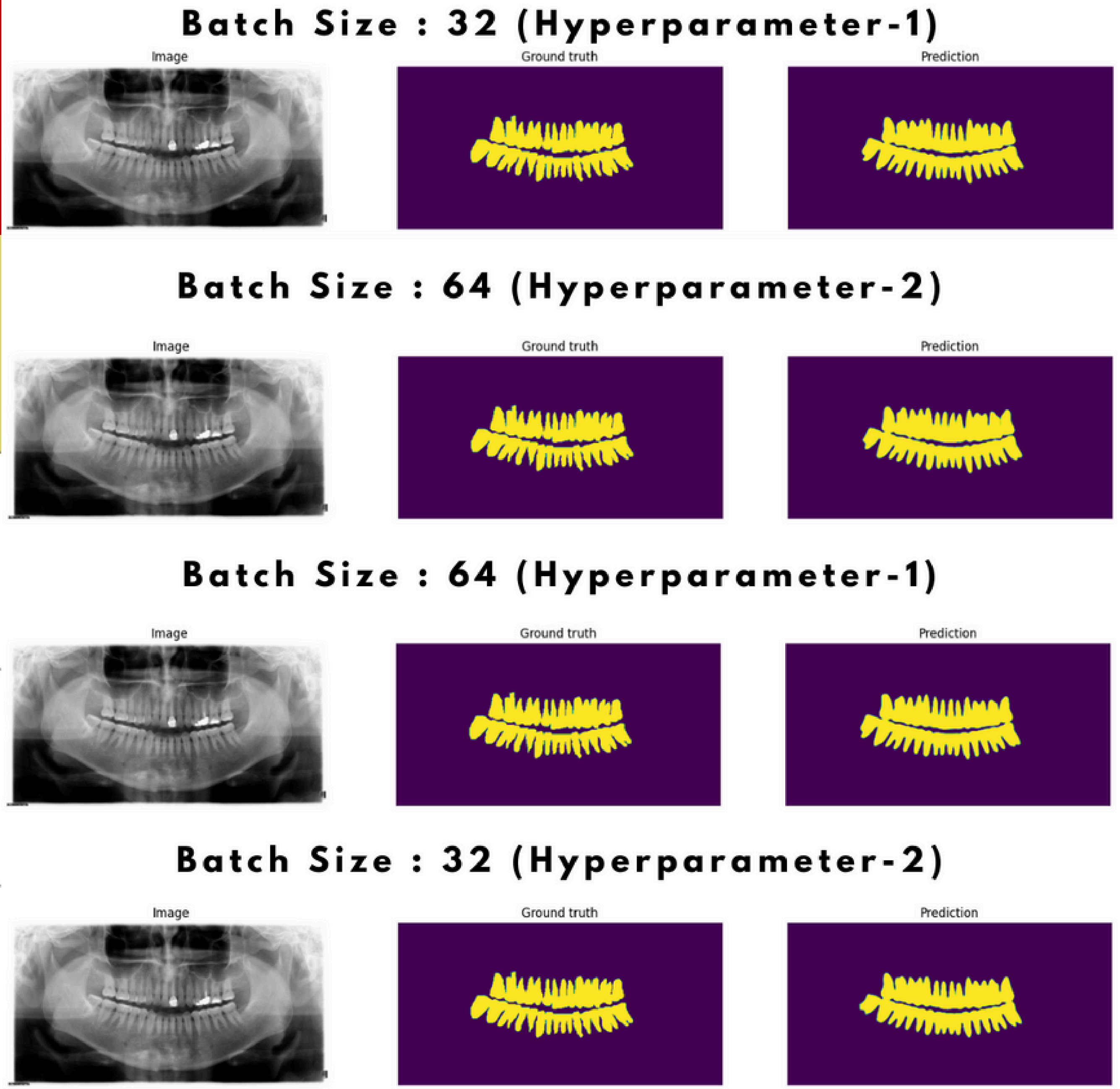
Rank	Architecture	Encoder	Test Dice	Test IoU	Test Accuracy	Average Score	Inference Time (s)
1	UNet++	ResNet34	0.9115	0.8387	0.9793	0.9098	0.0280
2	UNet	ResNet34	0.9048	0.8273	0.9778	0.9033	0.0111
3	LinkNet	ResNet34	0.9050	0.8275	0.9777	0.9034	0.0393
4	UNet++	MobileNetV2	0.9026	0.8236	0.9771	0.9011	0.0309
5	DeepLabV3+	ResNet34	0.9028	0.8242	0.9773	0.9014	0.0224
6	PAN	ResNet34	0.9031	0.8263	0.9775	0.9023	0.0656
7	UNet	MobileNetV2	0.9036	0.8247	0.9772	0.9018	0.0594
8	LinkNet	MobileNetV2	0.8947	0.8112	0.9752	0.8937	0.0264
9	DeepLabV3+	MobileNetV2	0.8945	0.8111	0.9753	0.8936	0.0213
10	FPN	MobileNetV2	0.8922	0.8074	0.9747	0.8914	0.0174
11	DeepLabV3	ResNet34	0.8933	0.8088	0.9747	0.8923	0.0671
12	PAN	MobileNetV2	0.8884	0.8026	0.9742	0.8884	0.0209
13	PSPNet	ResNet34	0.8866	0.7976	0.9730	0.8857	0.0213
14	FPN	ResNet34	0.8835	0.7940	0.9728	0.8834	0.0379
15	DeepLabV3	MobileNetV2	0.8768	0.7821	0.9705	0.8765	0.0564
16	PSPNet	MobileNetV2	0.8760	0.7805	0.9705	0.8757	0.0182

- The models are ranked based on the average of Dice Coefficient, IoU, and Pixel Accuracy.

Results

- This table **summarizes the performance metrics** (Dice Coefficient, IoU, and Pixel Accuracy) on **Test set** for **ResNet34 model and hyperparam batch size 32/64 & several improvements**

Rank	Architecture	Batch Size	Dice Coefficient	IoU Value	Pixel Accuracy	Average
1	**U-Net**	**32**	**0.9049**	0.8274	0.9777	**0.9033**
2	U-Net (Hyperparam-2)	64	0.903507	**0.828257**	**0.97783**	0.9032
3	U-Net	64	0.90035	0.82090	0.97667	0.8993
4	U-Net (Hyperparam-2)	32	0.88062	0.78783	0.97228	0.88024



Hyperparameter :

-Input Size: 256 x 512

-Batch Size: 32 & 64

-Optimizer: Adam

-Learning Rate: 1e-3

-Scheduler: Reduce On Plateau

-Factor: 0.5

-Patience: 5

-Early Stopping: Patience 20

Then, Hyperparameter-2 :

-Learning Rate: 5e-4

-Scheduler: Reduce On Plateau

-Factor: 0.2

-Patience: 10

Using same model

3.Unet-Resnet34 (batch size: 32)

4.Unet-Resnet34 (batch size: 64)

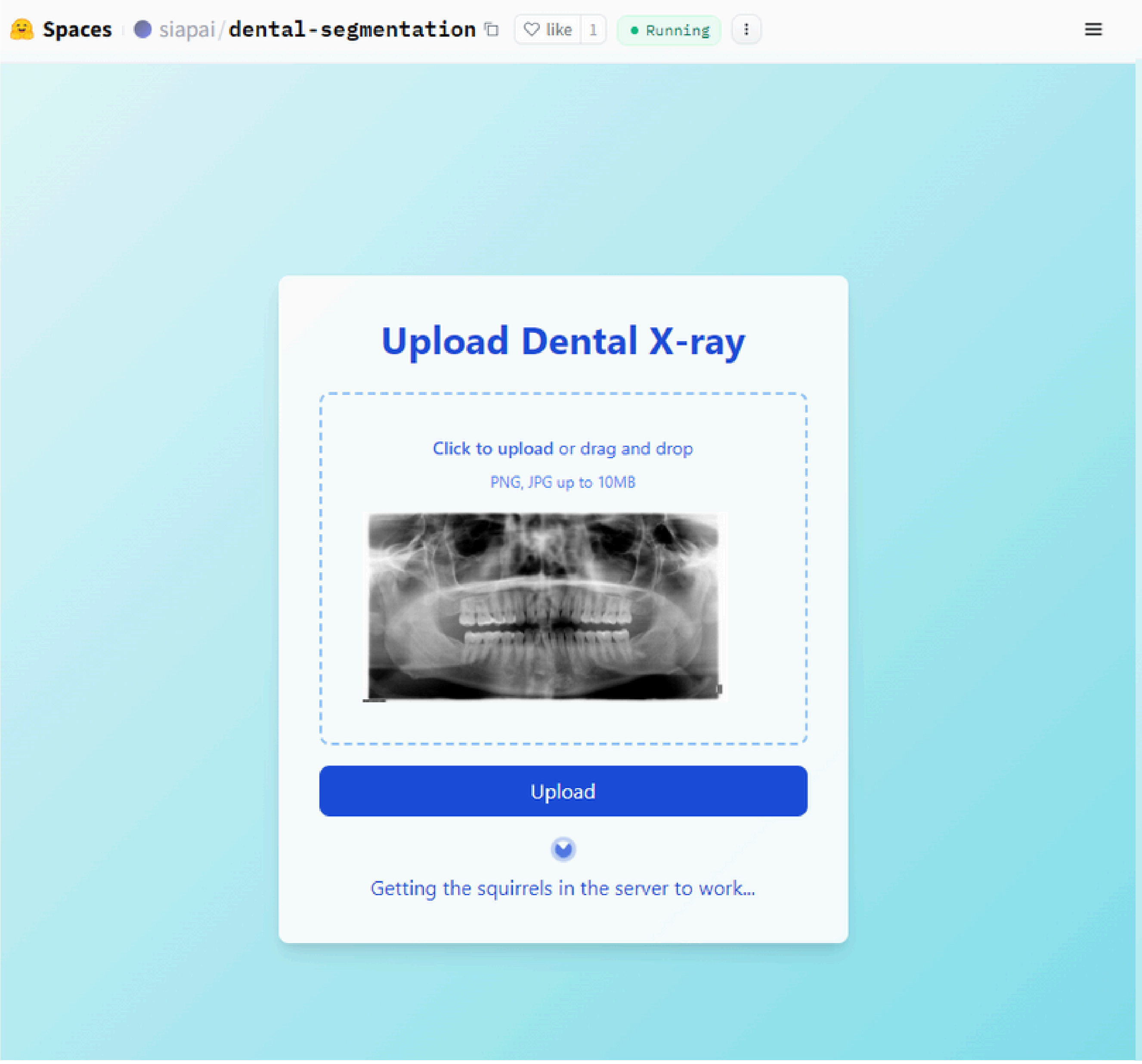
- The models are ranked based on the average of Dice Coefficient, IoU, and Pixel Accuracy.

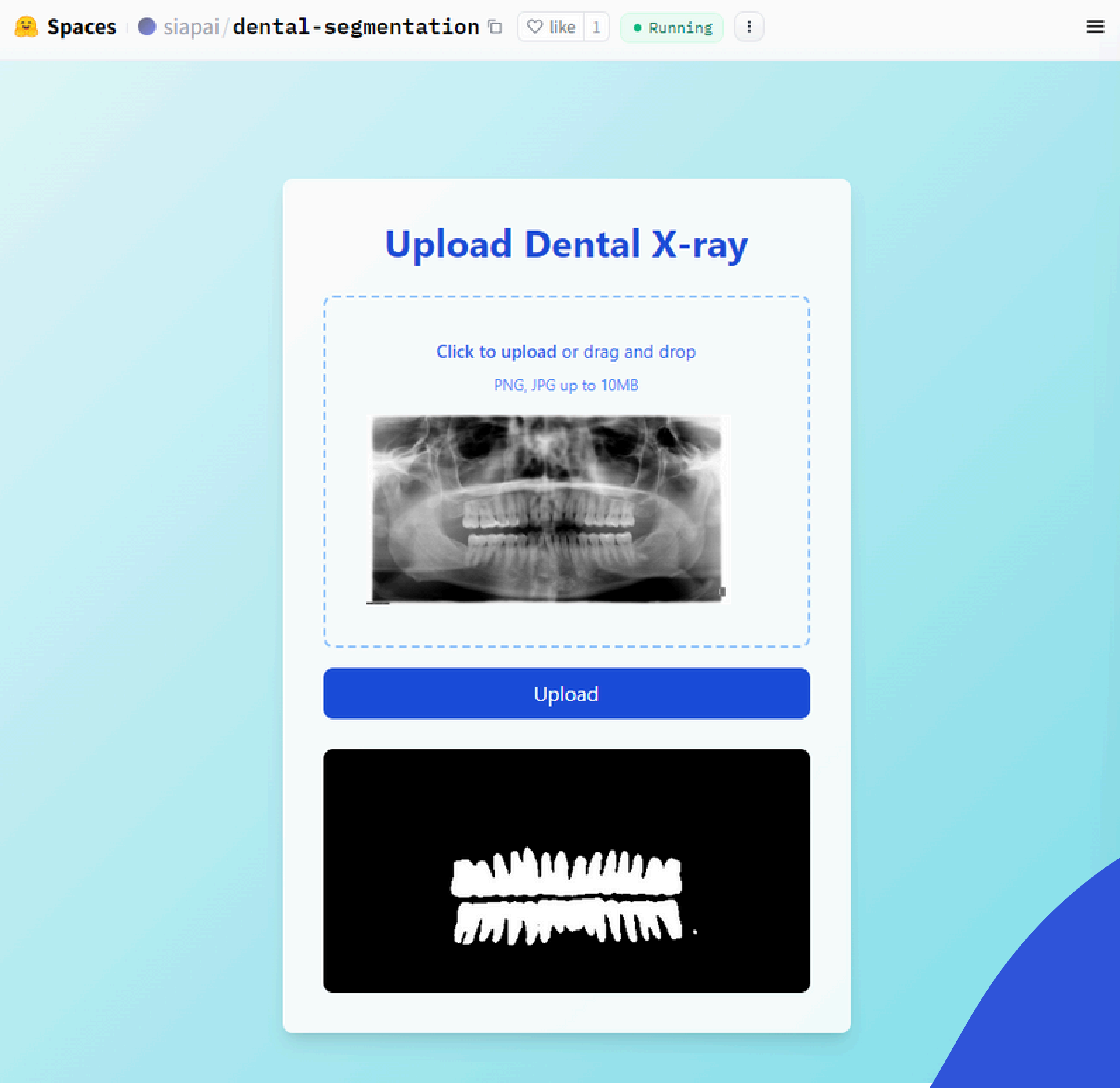
Deployment

- - Backend: fast api
- - Frontend: html+javascript
- - Container: docker
- - Cloud: HuggingFace space

>>> Try This Out

https://huggingface.co/spaces/siapai/dental-segmentation



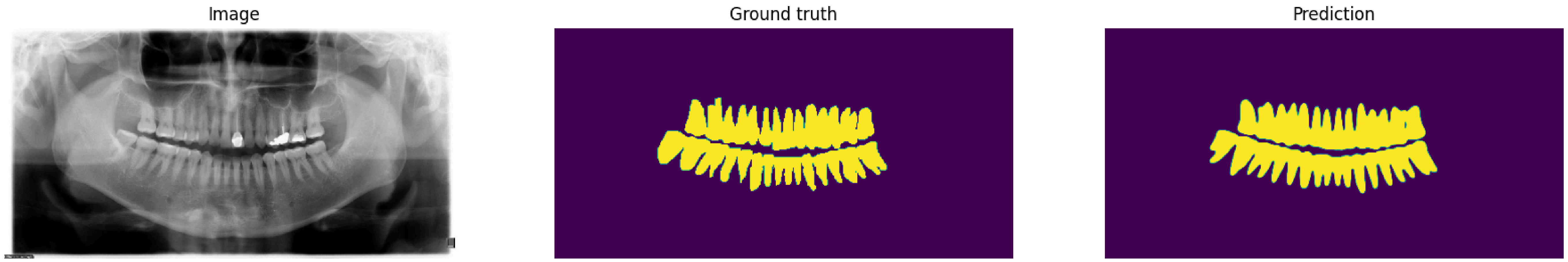


Conclusion

To find the best balance between performance and inference time, consider the following architectures:

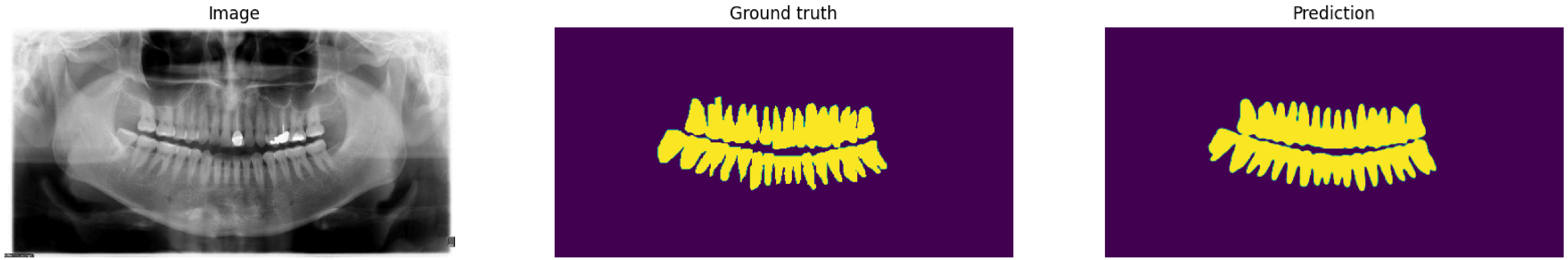
1.UNet++ with ResNet34

- Average Score: 0.9098
- Inference Time: 0.0280s



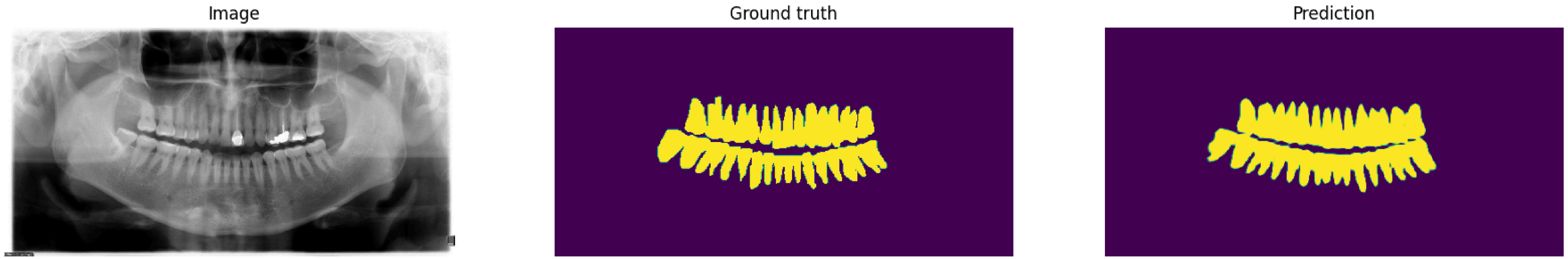
2.UNet with ResNet34

- Average Score: 0.9033
- Inference Time: **0.0111s**



3.DeepLabV3+ with ResNet34

- Average Score: 0.9014
- Inference Time: 0.0224s



UNet with ResNet34 is r**ecommended** for its **performance & fastest inference time**, making it highly efficient for real-time applications.

Future Improvement

The current model is only capable of performing semantic segmentation without classification.

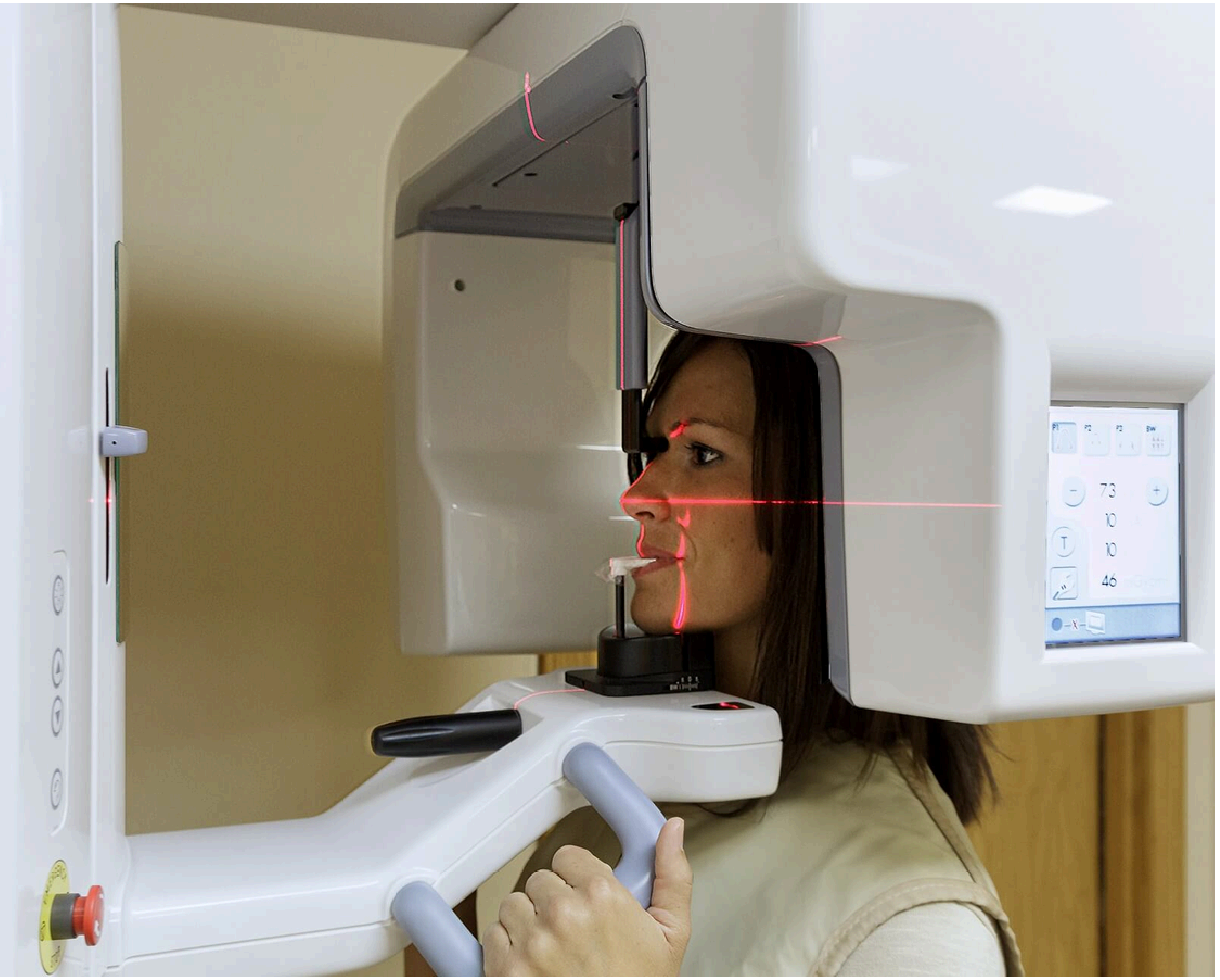
A.Integration of Segmentation and Classification

- The goal is to **extend** its **capabilities** to assist in **classifying several dental condition** by **performing both segmentation and labeling.**

- To enhance the model's utility by **providing detailed segmentation maps** along with class labels for each segment, thereby **addressing complex dental problems more effectively.**

Real-world Application

- **Embedded into digital X-ray machines, providing real-time feedback to dentists while capturing radiographs.**



- automate some of the workload currently handled by dentists, such as **analyzing routine X-rays.** This would **free up dentists' time to focus on more complex cases** and **patient interaction.**

Contact Us

Don’t hesitate to contact us for further inquiries or any collaborations.

Andrian Muzakki Firmansyah

Andrian Firmansyah

GitHub https://github.com/siapai/tuft-dental-segmentation/tree/main

M. Andhika Dwiki Nugraha

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GitHub https://github.com/AndhikaNugRah/DentalSegmentationUnetResnet