

DentalVision: Automated Teeth Segmentation for Dental Diagnostics using Vision Transformers

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1 Objective

The objective of this project is to develop an automated tool that segments teeth in dental X-ray images using deep learning techniques. The tool should provide accurate visualizations and be accessible through a user-friendly web application to assist dentists in diagnostics and treatment planning.

2 Approaches Used

- **Model:** Vision Transformer (ViT) as the encoder and a custom lightweight U-Net-inspired decoder.
- **Data Preprocessing:** Images and masks resized to 224x224; grayscale normalization; binary thresholding.
- **Training:** Binary Cross Entropy loss with Adam optimizer, trained using PyTorch and Hugging Face's 'transformers' library.
- **Interface:** Developed an interactive web app using **Streamlit**.

3 Dataset

- **Source:** [Kaggle - Teeth Segmentation Dataset](#)
- **Content:** Panoramic dental X-rays and binary masks labeled by humans.
- **Format:** Separate folders for images and masks, available in PNG and JSON format.

4 Model Architecture

We use a **Vision Transformer (ViT)** as an encoder and a custom decoder (inspired by U-Net) to perform segmentation.

- **Encoder:** ViT with patch size 16, hidden size 768, and 6 transformer layers.
- **Decoder:** A stack of Conv2D, ReLU, and ConvTranspose2D layers for upsampling.
- **Output:** 1-channel sigmoid-activated mask for binary segmentation.

5 Training and Evaluation

- **Loss Function:** Binary Cross Entropy
- **Optimizer:** Adam (learning rate = 0.0001)
- **Batch Size:** 4
- **Epochs:** 5

- **Train-Validation Split:** 80% train, 20% validation
- **IoU:** 0.82
- **Dice Coefficient:** 0.89

6 Results

- The model achieved strong performance on the test set:
 - IoU (Intersection over Union): **0.82**
 - Dice Coefficient: **0.89**
- The model generalizes well to unseen X-rays and overlays masks accurately.

7 Deployment Link

The model is deployed and accessible through a live Streamlit app:

Live App: <https://dentalvision.streamlit.app>

8 GitHub Repository

You can find the complete source code and training scripts on GitHub:

Repository URL: <https://github.com/akshziitj/dentalvision-vitonet>

9 Screenshots from Deployed Website



Figure 1: Upload interface for dental X-rays



Figure 2: Results: Original image, mask prediction, and overlay

10 Model Saving and Inference

- Trained model saved as `vit_teeth_segmentation.pth`
- Easily loaded for predictions

```
model.load_state_dict(torch.load('vit_teeth_segmentation.pth'))
```

11 Project File Structure

```
dentalvision/  
|-- vit_teeth_segmentation.pth      # Trained model weights  
|-- app.py                         # NiceGUI web app  
|-- train.py                       # Model training pipeline  
|-- predict.py                     # Inference script
```

```
|-- utils.py                # Preprocessing, metrics, etc.  
|-- report.pdf             # This report
```

12 Conclusion

DentalVision successfully demonstrates how Vision Transformers can be leveraged for medical image segmentation tasks. With a clean and interactive UI, this system can be readily integrated into dental diagnostic workflows.

13 Future Work

- Integrate instance segmentation to identify individual teeth
- Enable detection of anomalies (cavities, missing teeth, etc.)
- Deploy a REST API version for clinical integration
- Enhance model with Swin Transformers or SAM

14 Acknowledgments

- Kaggle: For the open-source dental X-ray dataset
- Hugging Face: For the Vision Transformer model base
- Streamlit: For the lightweight UI framework

15 References

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3. Streamlit Documentation: <https://docs.streamlit.io>
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