Dental Segmentation of The Mandible Using AI

Khushi Gohel

2/25/23
Inspirit AI Research Project

Abstract

Dental segmentation can help with decision-support issues in medical diagnosis, such as human identification and maxillofacial surgery, as well as orthodontic therapy, implant planning, and other issues. This leads to my research question; “How do I automate the task required to diagnose a dental problem during a dental visit?” The approach to solve this was to train an AI with images pre-segmented by experts and then test it. This process is also called image segmentation. The AI had eventually gotten a test accuracy score of 0.940 and test IoU score of 0.904. The closer to one that these scores are the better. Pixel accuracy and Iou score were surprisingly similar. I think that this is a good thing because it means both seem pretty accurate. The AI has its flaws but it can segment images when given images.

1. Introduction

The problem this paper strives to answer has a domain of dental images and helping dentists. By having the AI outline the mandible it helps facilitate diagnosis and registration of dental records. This can help dentists reach more patients faster. Dental segmentation can aid in decision-support for a variety of medical diagnosis problems, including human identification, maxillofacial surgery, orthodontic treatment, implant design, and other problems. Dentists can assist more patients if they spend less time on unnecessary chores. Both patients and dentists can gain from creating a tool that they can use. One restriction is that the quantity of photographs needed necessitates expert annotation. This will only work if the dataset has already identified the different problems or if a dentist manually points out the problems. Getting the code to work is another.

2. Background

Dental professionals use panoramic X-rays of the oral cavity before, during, and after treatments to deal with radiography in their daily practice [3,4,5,7]. This provides them with a crucial diagnostic tool that offers proof of disorders such dental caries, periapical lesions, or odontogenic cysts that are sometimes difficult to see with the naked eye. They anticipate that using AI into dental radiography would significantly improve the accuracy of the diagnosis and treatment plan because it plays a significant role in patient care.

DENTECT was developed to bring these ideas to life [6]. Although DENTECT is trained on only 1005 images, the annotations supplied by experts provide satisfactory results for both treatment and enumeration detection. DENTECT. In medical imaging this number drops substantially because it is far too difficult to annotate raw data. It is recognized that the dataset size is usually around 1000 which is quite low compared to fields outside of medical imaging. Even with this amount of data, DENTECT works considerably good. If the dataset size were to increase, the performance of DENTECT would improve drastically.

In our model one limitation we faced with having a small dataset is that the model becomes sensitive to noise and defects in the data. To address this limitation we manipulated the images and then fed it back into the code. Another way to go about this problem would be to get more images that are annotated by experts to feed into the code. We also used help from Tensorflow to do this.The amount of images needed, also need to be annotated by experts .This will only be possible if the dataset has already marked out the different problems or a dentist has to do it manually. Most of the articles I read say that classification of images would be a good method to recognize the problems of the mouth. All of this classification in dental x-rays could help dentists diagnose patients more accurately and quickly.

3. Dataset

We used the data set from the “Panoramic Dental X-rays With Segmented Mandibles” [3] set which was originally studied in [7]. Our image data consisted of panoramic x-rays.We had 116 images to split into a training and testing dataset. 64 images for training and 52 for testing. The only problem with our data set was that the article said it was two experts who separately segmented the images. However, the images that were claimed to be manually segmented by two different dentists were segmented exactly the same. Therefore, we could only use half of the dataset which was 116 images. Figure 1 shows an example of the manually segmented mandible from the data set.

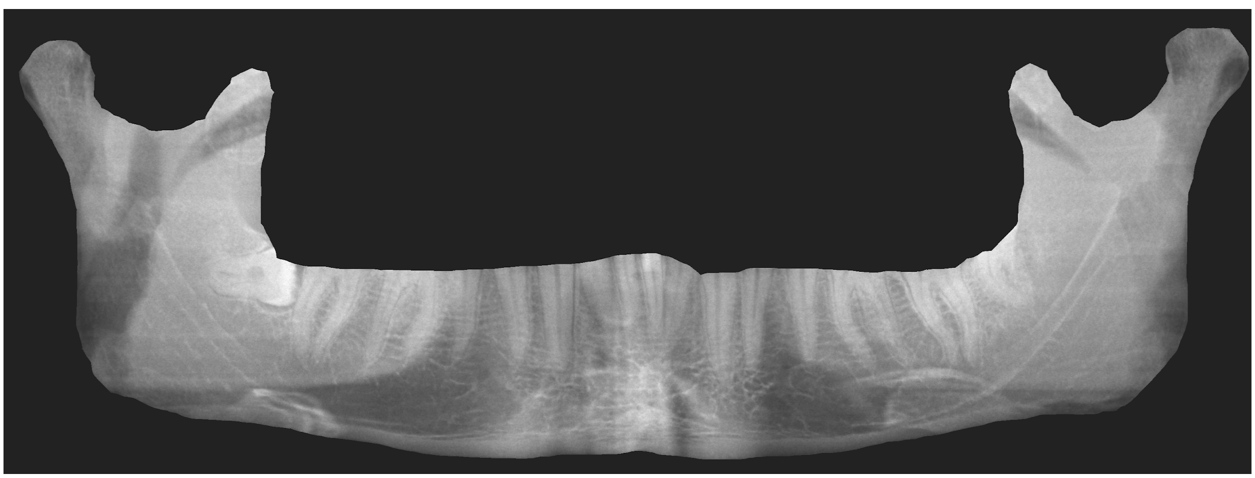


Figure 1: Image 98 which is a manually segmented mandible from the data set.

The process of segmenting an image into various regions or segments, each of which represents a different object or aspect of the image, is known as image segmentation. Using supervised or unsupervised learning approaches, machine learning algorithms like Convolutional Neural Networks (CNN) can be trained to automatically segment images based on a set of predefined features. An input image is the original image that needs to be segmented into multiple regions or objects of interest. A true segmentation is a correctly segmented image that accurately separates different regions or objects in the input image. A true mask is a form that obscures everything below it, leaving only the contents of the clipping path visible. Figure 2 shows an example of an original image, manual segmentation, and associated mask. To use a

CNN we then had to resize the images to 128x128 pixels, as shown in Figure 2.

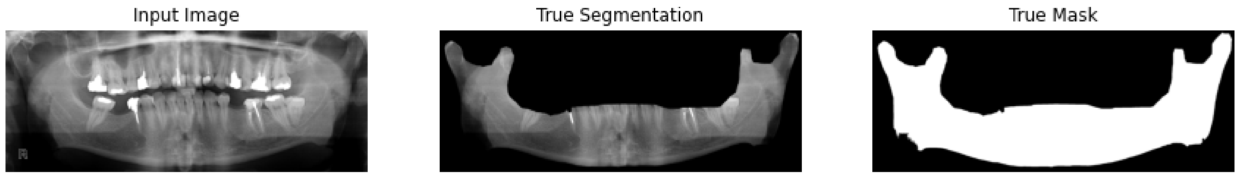


Figure 2: Image 21, its true segmentation, and its true mask.

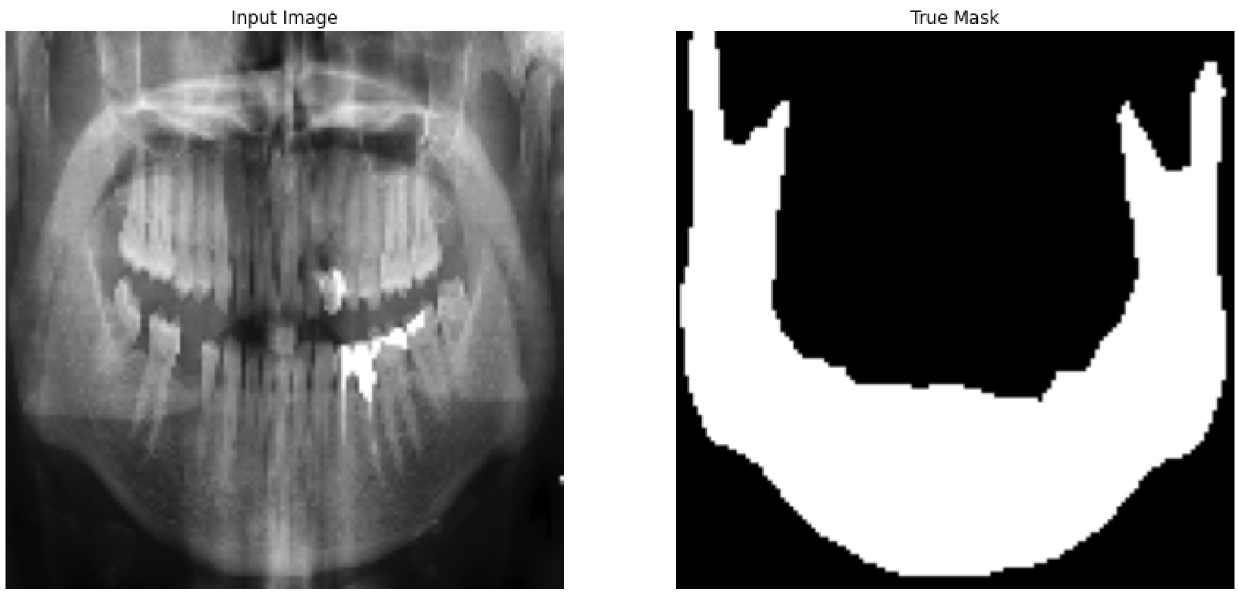


Figure 3: Example image and mask resized to 128x128 pixels for training.

4. Methodology / Models

In an image classification task, the network gives each input image a label (or class). But let's say you're interested in learning more about the object's shape, which pixel corresponds to which object, etc. In this situation, segmentation is the process of giving each pixel in the image a class. An image segmentation model provides significantly more in-depth data about the image. Image segmentation has a wide range of uses, including satellite imaging, self-driving automobiles, and medical imaging, to mention a few.

First to train an image segmentation model we followed the Tensorflow image segmentation tutorial [2]. The tutorial went through the steps of processing the data, defining the model parameters, training the model, and evaluating the performance. First we had to process the data. Then we split the data into training and testing data and then we augmented the data. The model we used consisted of two parts: the encoder, and the decoder. The specific architecture is shown in Figure 4. The encoder takes an image (128x128) and returns a handful of useful features. For this project we used a pre-trained MobileNetV2 model as the encoder and did not modify the weights. The decoder takes the features from the encoder and learns to output the segmentation mask for the image. The training process modifies the weights of the decoder only. For training the model we used Tensorflow, a batch size of 64 and 30 epochs.

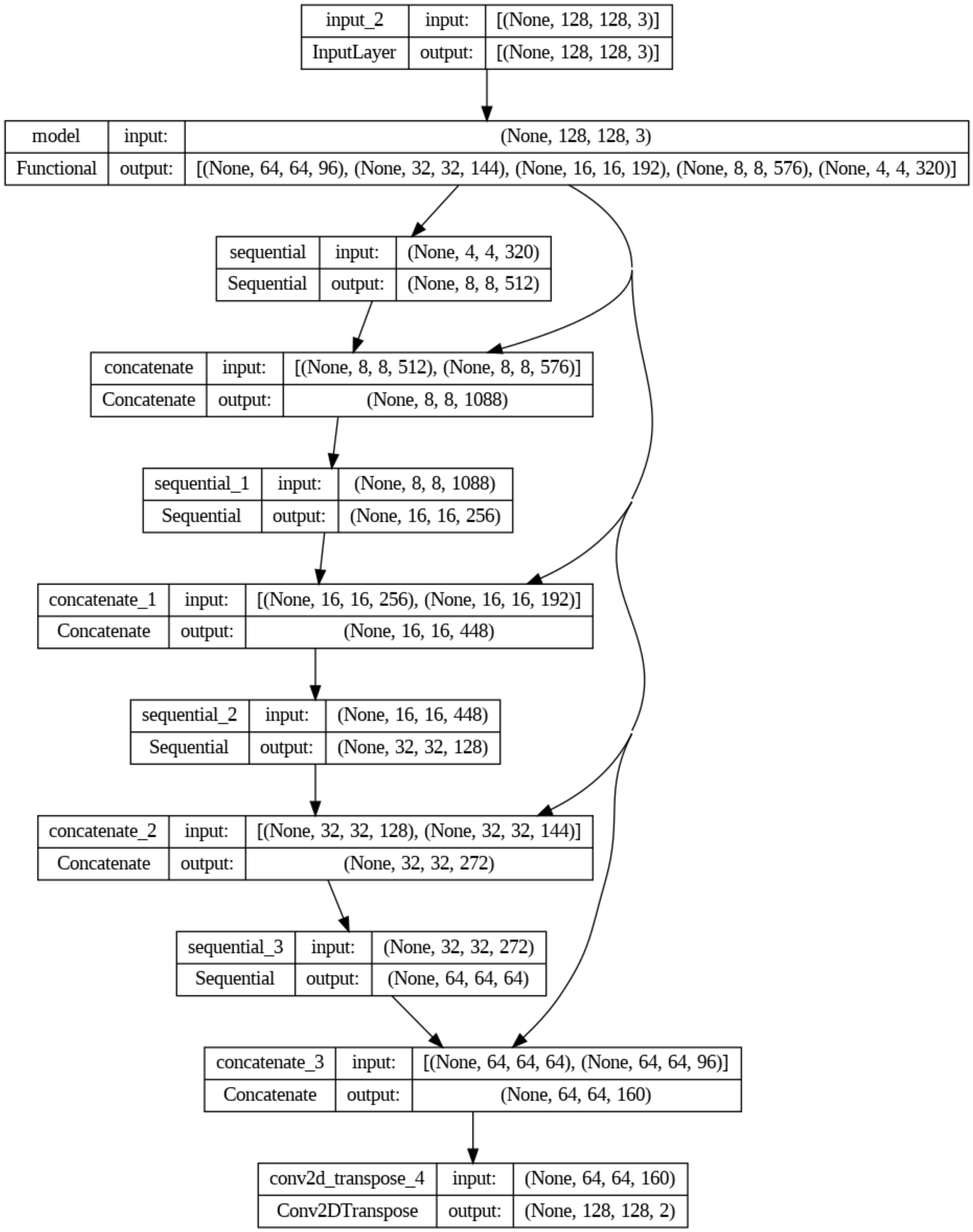
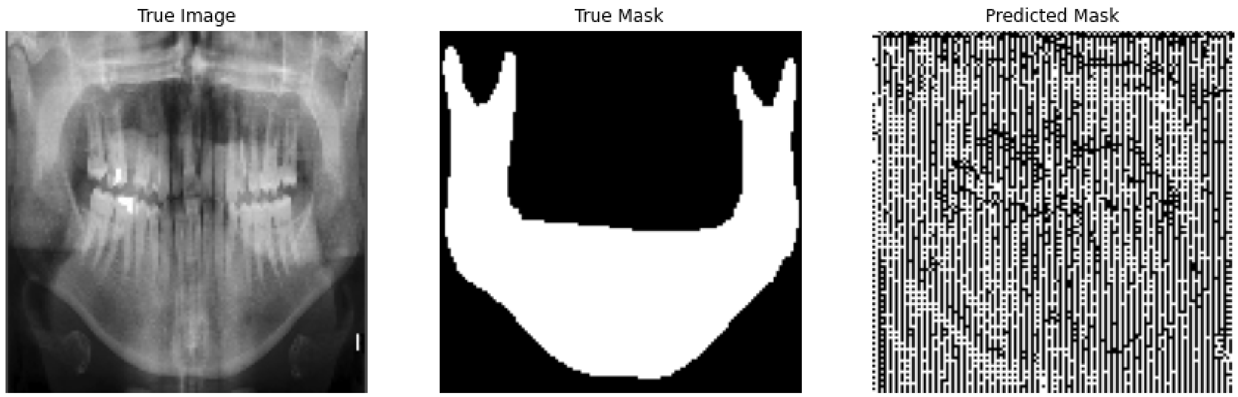


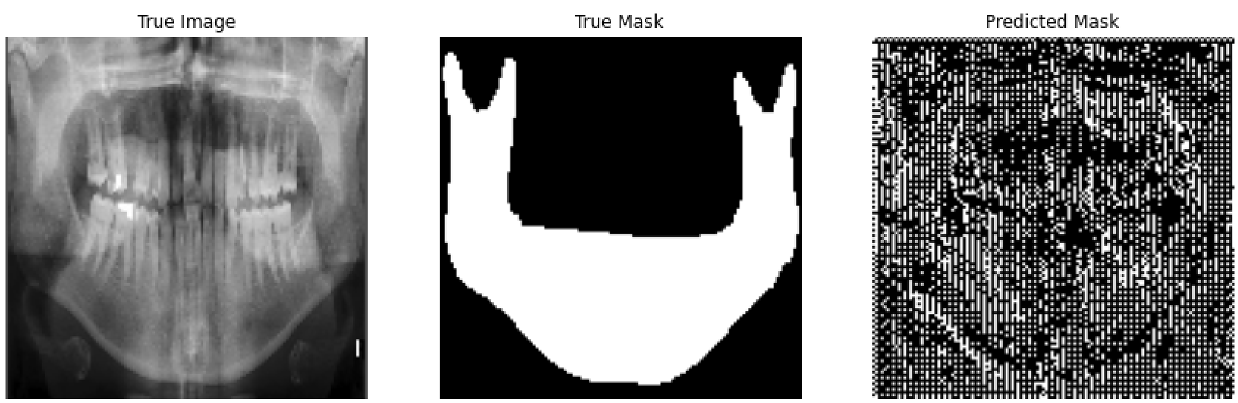
Figure 4: This is the architecture of our model.

5. Results and Discussion

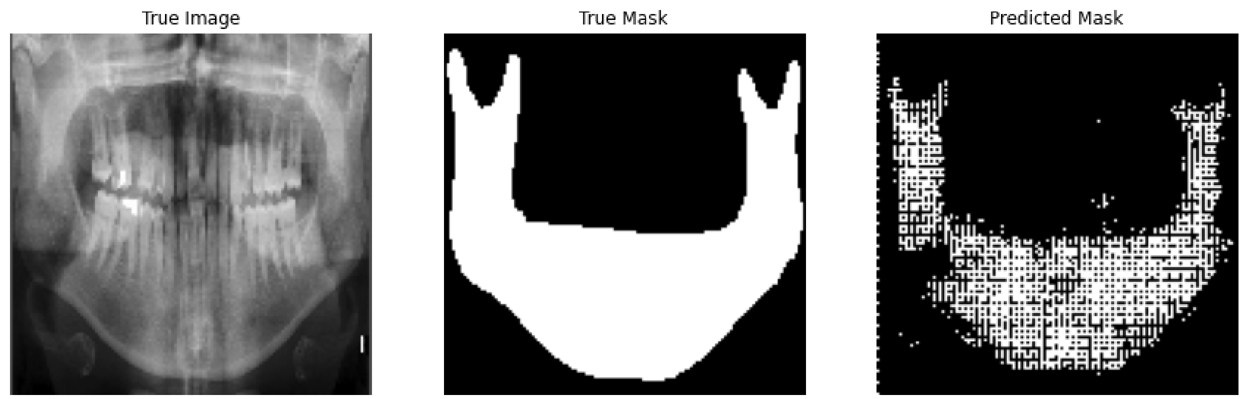
Figure 5 shows how the AI performs at different epochs. An epoch is the total number of iterations required to train the machine learning model using all of the training data at once. The sample prediction after epoch 30 had an accuracy score of 0.956.



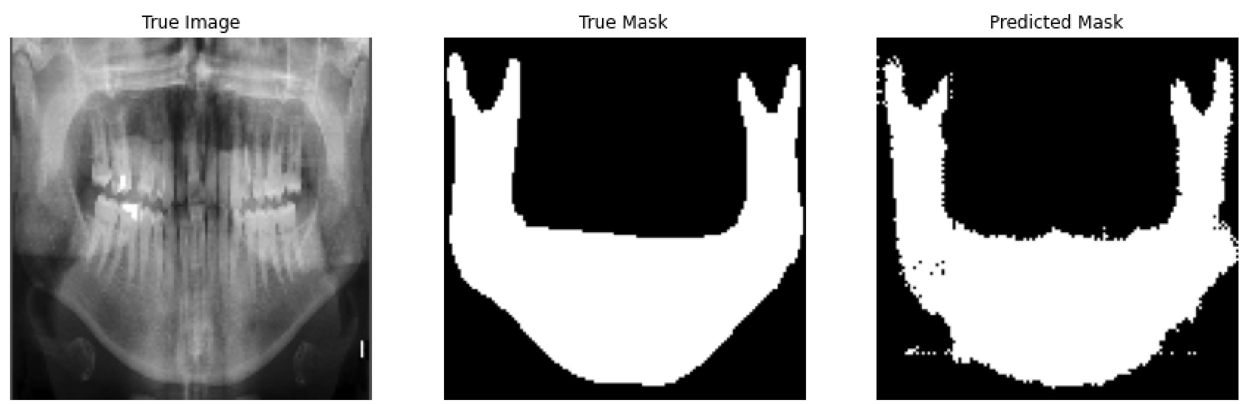
Epoch 1/30
1/1 [==============================] - 0s 63ms/step



Epoch 10/30
1/1 [==============================] - 0s 73ms/step



Epoch 20/30
1/1 [==============================] - 0s 67ms/step



Epoch 30/30
1/1 [==============================] - 0s 98ms/step

Figure 5: Here the performance of the model during training is visualized. First the model prediction is not coherent. Then, as the model trains for more epochs, the predictions become closer to matching the ground truth.

Figure 6 shows the training loss curve. It is pretty good because the plot of training loss decreases to a point of stability.[1]

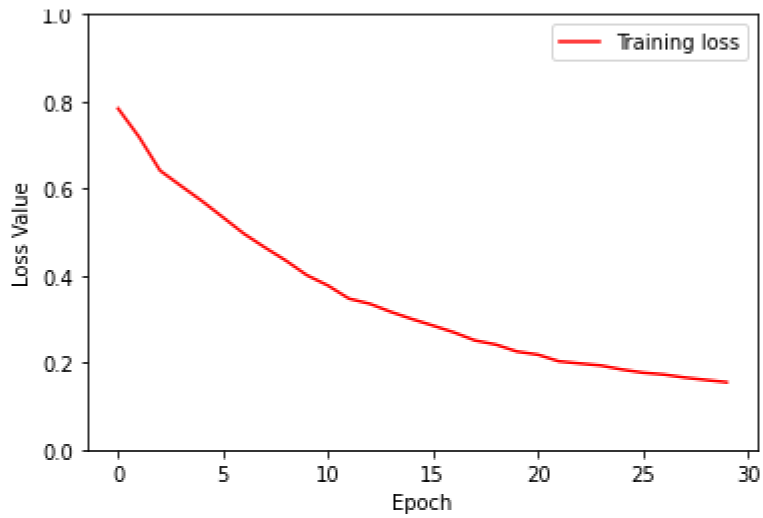


Figure 6: Training loss decreases with each epoch, but eventually flattens out. We stop training before 30 epochs to avoid overfitting.

A machine learning model that has been trained on a collection of annotated images produces the predicted mask. The model gains the ability to recognize the patterns and features in the images that are connected to various items or areas of interest during the training phase. After training, the model can be used to provide predicted masks for images.

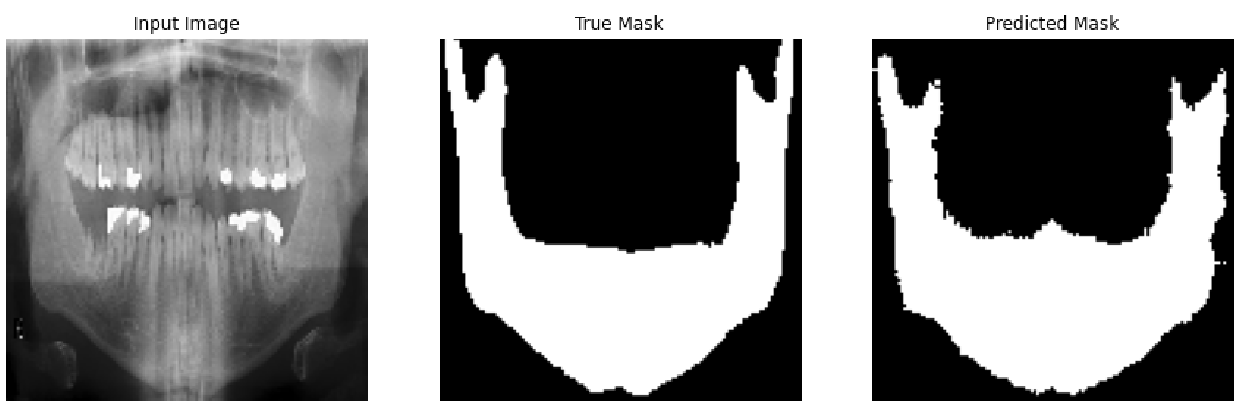


Figure 7: This is a random input image, its true mask and predicted mask..

In Figure 7 an example prediction for a test set image is compared with the true mask. The predicted mask has an accuracy of 0.940 and an IoU of 0.904. Pixel accuracy is a simple evaluation metric that calculates the percentage of correctly classified pixels, while IoU score is a more advanced evaluation metric that measures the overlap between the predicted and ground truth segmentation masks.

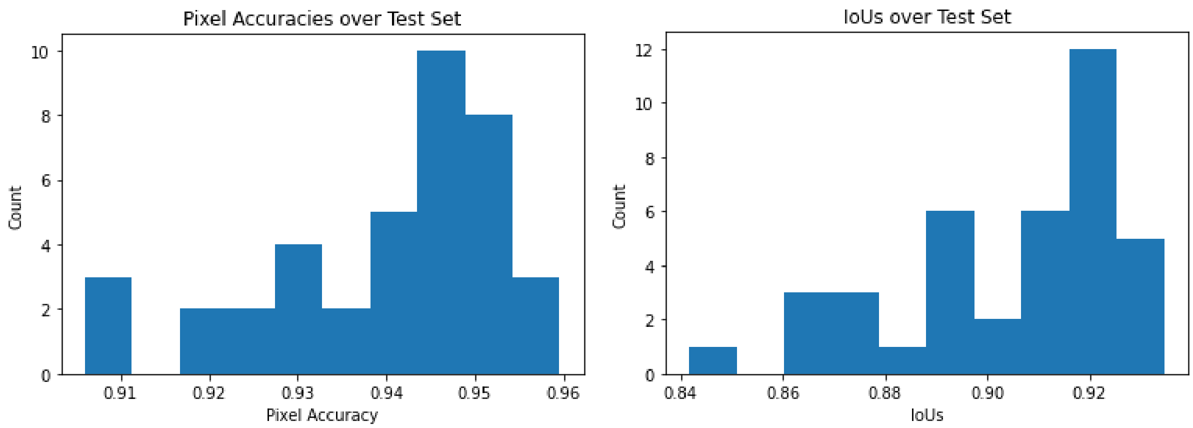


Figure 8: The distribution of pixel accuracy and IoU over the test set images are similar, meaning that choosing either metric for evaluation will yield similar results.

In Figure 8 we compare how pixel accuracy and IoU are distributed over the test images. Both scores are similar which is assumed to be a good thing. The AI had gotten a test accuracy score of about 0.94 and test IoU score of about 0.90.

6. Conclusions

The goal was to create a tool to help dentists segment images faster. We used image segmentation to achieve this goal. It was able to segment images but there is room for improvement. One thing it could improve is the boundary. Currently it produces a jagged boundary however a smoother boundary is more realistic. The model performed like it did due to a limited dataset. If I had to redo this experiment I would make sure to add more images into the dataset.

Acknowledgments

Thanks to the Society of Photo-Optical Instrumentation Engineers for allowing us to use their data set. Thanks to Inspirit AI, Joe Vincent, my family, and tensorflow for helping make this paper possible.

References

1. Brownlee, J. (2019) *How to use learning curves to diagnose machine learning model performance*, *MachineLearningMastery.com*. Available at: https://machinelearningmastery.com/learning-curves-for-diagnosing-machine-learning-model-performance/ (Accessed: February 21, 2023).
2. *Image segmentation : Tensorflow Core* (no date) *TensorFlow*. Available at: https://www.tensorflow.org/tutorials/images/segmentation (Accessed: February 21, 2023).

3. Abdi, A. (2020) *Panoramic Dental X-rays with segmented mandibles*, *Mendeley Data*. Mendeley Data. Available at: https://data.mendeley.com/datasets/hxt48yk462/2 (Accessed: February 25, 2023).
4. *ODSI-DB – oral and Dental Spectral Image Database* (no date) *Spectral*. Available at: https://sites.uef.fi/spectral/odsi-db/ (Accessed: February 25, 2023).
5. *Mono – a database for Dental Image Diagnostics* (no date) *MONO – A Database for Dental Image Diagnostics IADR Abstract Archives*. Available at: https://iadr.abstractarchives.com/abstract/19iags-3180577/mono--a-database-for-dental-image-diagnostics (Accessed: February 25, 2023).
6. Yüksel, A.E. *et al.* (2021) *Dental enumeration and multiple treatment detection on panoramic X-rays using Deep Learning*, *Nature News*. Nature Publishing Group. Available at: https://www.nature.com/articles/s41598-021-90386-1 (Accessed: February 25, 2023).
7. Abdi, A.H., Kasaei, S. and Mehdizadeh, M. (2015) *Automatic segmentation of mandible in panoramic X-ray*, *Journal of medical imaging (Bellingham, Wash.)*. U.S. National Library of Medicine. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4652330/ (Accessed: February 25, 2023).