Segmentation of Teeth from Child X-ray Panoramic Dental Images

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***Özetçe* —Diş röntgenlerinin analizi, klinik işlemlerde, hastalığın teşhisi için çok önemli ve temel bir işlemdir. Dental radyolojide diş numaralandırması zaman alan rutin bir değerlendirmedir. Günümüzde diş röntgenleri, diş teşhisi ve diş tedavisi vs. için kullanılmaktadır. Örneğin, rutin diş prosedürlerinde, maksillofasiyal cerrahi uygulamalarda ve diş jenerik modellemesinde insan diş görüntülerini tanımlamak için dişlerin numaralandırılması gereklidir.**

Bu proje, muayene sürecinde, profesyonellerin iş yükünü azaltmak için, röntgen üzerindeki dişlerin segmente edilmesi ve tipinin tanımlanması işini otomatize etmek amacıyla, input olarak verilen röntgenler üzerindeki dişleri mask-RCNN algoritması kullanarak segmente edecek ve dişin türünü tespit edecektir.

Anahtar Kelimeler—segmentasyon, mask r-cnn, cnn, sınıflandırma, yapay sinir ağları

***Abstract*—The analysis of dental X-rays is a very important and fundamental process for the diagnosis of disease in clinical procedures. Tooth numbering is a time-consuming routine evaluation in dental radiology. Today, dental X-rays are used for dental diagnosis and dental treatment. For example, numbering of teeth is necessary to identify human tooth images in routine dental procedures, maxillofacial surgical practices, and dental generic modeling.**

This project will segment the teeth on the X-rays given as input using the mask r-cnn algorithm and determine the type of tooth in order to automate the job of segmenting and identifying the type of teeth on the X-ray in order to reduce the workload of professionals during the examination process.

Keywords—segmentation, mask r-cnn, cnn, classification, artificial neural network.

I. Introduction

In dentistry, radiological examinations offer assistance masters by appearing structure of the tooth bones with the objective of screening inserted teeth, bone anomalies, blisters, tumors, contaminations, breaks, issues within the temporomandibular regions, just to quote a couple of. In some cases, depending exclusively within the specialist's conclusion can bring contrasts within the analysis, eventually preventing the treatment. In spite of the fact that devices for total programmed conclusion are no however anticipated, picture design acknowledgment has advanced towards choice bolster, primarily beginning with the discovery of teeth and their components in X-ray pictures.

Tooth location has been protest of investigate amid at slightest the final two decades, basically depending in edge and region-based strategies. Taking after a distinctive heading, this paper proposes to investigate a profound learning strategy for occasion division of the teeth. To the leading of our information, it is the primary framework that identifies and portion each tooth in all encompassing X-ray pictures.

X-rays are a valuable resource that helps dentists diagnose cysts, tumors, fractures, and other conditions that require more information than that is possible to gather by directly examining the patient[1].

For the reasons stated above, various approaches for automated X-ray analysis involving tooth detection and classification,tooth segmentation and many methods have been proposed.

In this paper, we clarify the application of mask r-cnn on automatic tooth detection and segmentation. Mask r-cnn is a recently proposed surprise algorithm for object detection and semantic segmentation. This paper points at recognizing and portioning tooth only. We appear that mask r-cnn too show a good segmentation impact in complex and crowded teeth structures. We utilize the pixel accuracy (PA) to assess the comes about.

II. Related Work

In the literature, there are many dental image analysis studies for tooth segmentation. Some of them uses 3D segmentation because, traditional geometry-based methods tend to receive undesirable results due to the complex appearance of human teeth (e.g., missing/rotten teeth, feature-less regions, crowding teeth, extra medical attachments, etc.)[2][3].

In the other hand, like in this project, studies of 2D segmentation via mask r-cnn is also preferred. Dental records play an important role in forensic identification. To this end, postmortem dental findings and teeth conditions are recorded in a dental chart and compared with those of antemortem records. However, most dentists are inexperienced at recording the dental chart for corpses, and it is a physically and mentally laborious task, especially in large scale disasters. The goal is to automate the dental filing process by using dental x-ray images.[4][5].

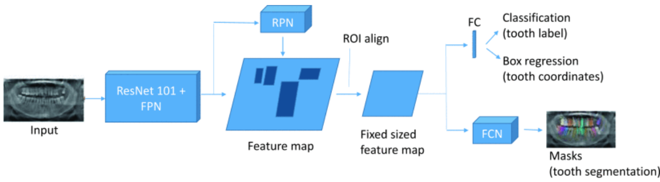


Figure 1 Mask R-CNN

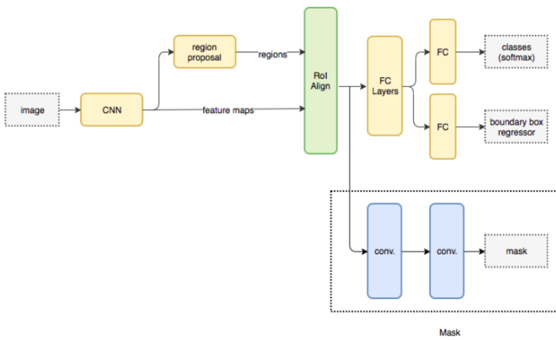


Figure 2 Working Principle of Mask R-CNN[7]

III. The Method

Mask R-CNN, one of the deep neural network methods, will be used to segment and classify the teeth. It is proposed for simultaneously segmenting objects and detection by extending the Faster RCNN framework.

Mask RCNN is very useful for simultaneous detection, labeling, and segmentation of teeth with the correct parameter and extraction architecture. It owes simultaneous detection to faster RCNN. As shown in Figure 1 and 2, after the creating ROI align layer, the network can extract multiple ROI boxes and focus on those boxes. It detects the potential ROI's and stores them in the ROI pool on the study of the deep residual network[6]. After then, those ROI's are fitted to the object.

Detectron2, which is a platform for object recognition, segmentation, image recognition[8] is used to implement mask r-cnn. In order to train on the data set with the mask r-cnn method with the Detectron2 library, it is necessary to divide the data set into train and test, mark the objects to be classified on the images in this set, and generate a json file in MS COCO[9] format. In this process, labelme[10] and labelme2coco[11] libraries used to annotate the dataset and converting those annotations to COCO format.

Our goal was to create bounding frames around the teeth, to segment teeth correctly in panoramic photographs, to display masks in pixel degrees and to specify the classes of the teeth as shown in Figure 3.

In order to implement the presented method, a panoramic dataset containing 170 images provided by IvisionLab is used[4]. 3 images among them has been removed due to does not meeting requirement to be child teeth X-rays.

The dataset has the panoramic images and the segmentation masks as shown in Figure 4.

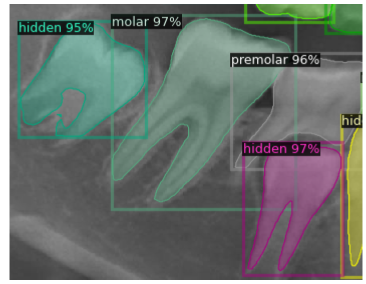
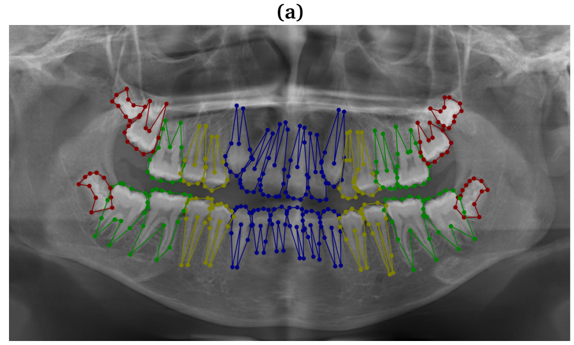


Figure 3 Bbox, segmentation and class of teeth

(a)



(b)

Figure 4 An example of a panaramic dental image and its mask

The model was trained from a total of 167 children's dental X-rays. In the data set, there are 4 tooth types in total, including molars, premolars, embedded and front teeth (Canine teeth are included in the front teeth class). Of the data which annotated, %70 (116 images) was used for train and %30 (51 images) was used for testing. 2000 iterations were determined for the training, roi heads batch size was chosen as 64 and the learning rate was chosen as 0.002.

IV. Experiments

In order to evaluate the presented method, %30 percent (51 images) of the data set was used for testing. This set has 1971 instance as shown in Table 1.

	molar	hidden	premolar	front	total
Instances	274	724	386	587	1971

Table 1 Number of tooth samples by its class in test set

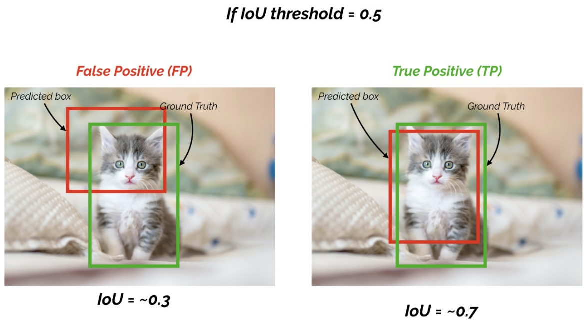


Figure 5 Intersection of Union (IOU)

Figure 6 Binary Mask Example

To evaluate a prediction in object detection, IOU or Jaccard index is used as a metric to understand whether the estimation is correct. (See Figure 5) If the IOU ratio is higher than the specified threshold, the prediction is considered correct (true positive), otherwise incorrect (false positive).

Average precision (AP) determines the accuracy of the recognition process according to the specified IOU threshold. Table 2 and 3 contains these values for this model.

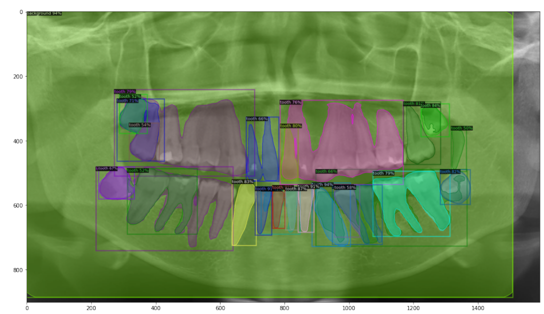
AP50, AP75, etc. expressions mean the AP value calculated according to different IOU thresholds (0.5, 0.75, etc.). The mAP metric is calculated by averaging the calculated AP values for each class. In theory, it is desirable that the AP value be %100, but in practice it is difficult to reach this value.

	molar	hidden	premolar	front
bbox AP	67.182	64.069	57.787	61.413
segm AP	61.997	57.937	54.688	52.953

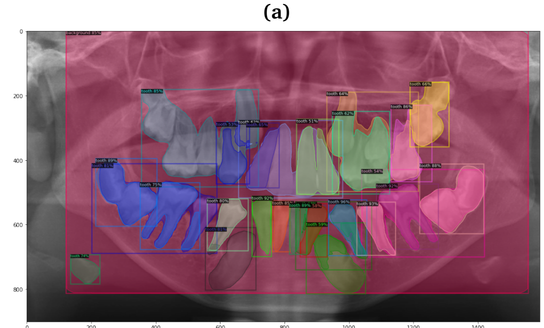
Table 2 AP values per class

	AP	AP50	AP75	APm	APl
for bbox	62.612	91.968	77.795	67.995	61.814
for segm	56.894	92.087	69.773	58.186	58.340

Table 3 Evaluation results



(a)



(b)

Figure 7 Experimental Outputs (1)

In early development of this model, the results was not bright as it should be. The model which trained with binary masks as shown in Figure 6 was not able to correctly segmentate teeth. (See Figure 7)

But it can be said that after manual annotation of the masks via labelme, the final results were promising. (See Figure 8, 9 and 10)

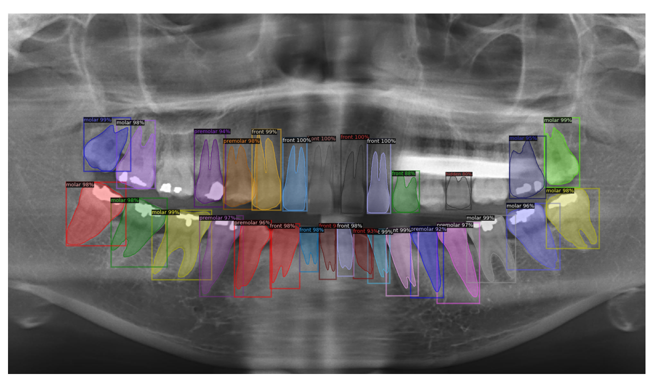


Figure 8 Final Output (1)

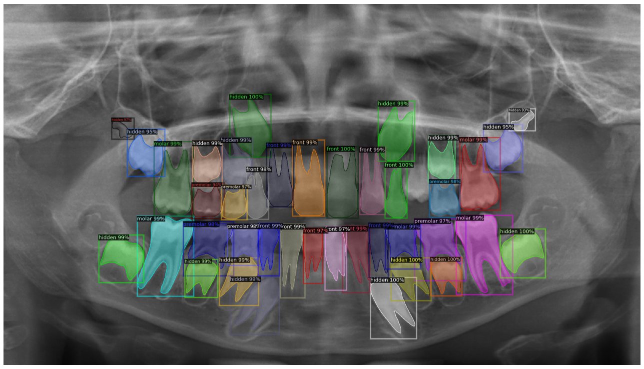


Figure 9 Final Output (2)

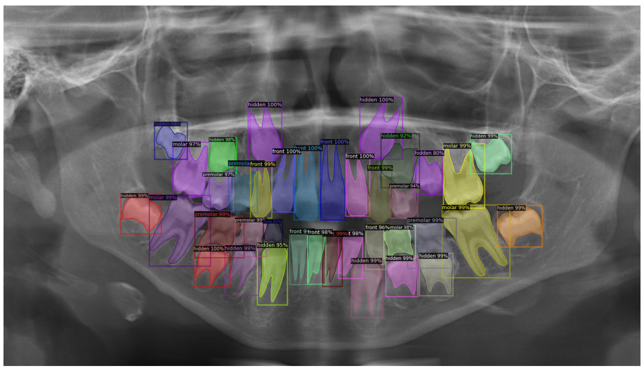


Figure 10 Final Output (3)

V. Conclusions

The aim of the project is to provide convenience to dentists when examining pediatric patients.

As children grow, milk teeth fall out and permanent teeth are placed in their place. The patient may have milk teeth and permanent teeth together. Some milk teeth may be lost, and permanent teeth may not be placed in their place yet. Some impacted teeth may be in an inconspicuous position. In order to facilitate the analysis of such different situations, a model has been developed that will process the X-ray images, segment the teeth in the X-ray image and determine which type of teeth these teeth are.

The mask r-cnn algorithm was used for the model, the data set provided by IvisionLab was used for the training process, and the detectron2, labelme, labelme2coco libraries on the python programming language were used for the implementation.

Considering that deep learning algorithms require a high amount of data for the training phase, the performance of this model (See Table 2 and 3), which is trained with a total of 167 images as train and test, can be improved by increasing the quantity and quality of the data set.

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