Detection of Ectopic Eruption Effects on 1st and 2nd Molar Teeth Using Deep Learning Methods

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Özetçe —**Ektopik Erupsiyon dişlerin normal diş pozisyonundan saparak ağızda anormal bir pozisyonda çıkmasıdır. Bu durum genellikle üst çenenin azı dişlerinde gözükür. Bu dişler 55 ve 65 numaralı süt dişleri ile 16 ve 26 numaralı kalıcı azı dişleridir. Alt çenede ise 75 ve 85 numaralı süt dişleri ile 36 ve 46 numaralı kalıcı azı dişlerinde az da olsa ektopik erupsiyon görülmektedir. Çocuklarda süt azı dişinin altından çıkan kalıcı azı dişinin ektopik erupsiyona neden olup olmadığının erken aşamada tespiti uygulanacak tedavi açısından önemlidir. Bu projede derin öğrenme yöntemleri kullanılarak bu dişlerde ektopik erupsiyon görülüp görülmediğini şiddetiyle beraber tespit edip kullanıcının bilgisine sunan bir uygulama geliştirilmiştir. Uygulamanın klinik ortamda hekimler tarafından kullanılması planlanmıştır. İlk olarak Mask R-CNN modeli kullanılarak radyografi görüntüsünde bulunan azı dişleri kırpılmıştır. Daha sonra tespit edilip ikili gruplar halinde (azı dişi ve yanındaki süt dişi) kırpılan bu azı dişleri DeiT ve BeiT kullanılarak geliştirilen ikili sınıflandırma modeline verilmiştir. İkili sınıflandırma modeli ile verilen diş ikilisinde ektopik erupsiyon olup olmadığı tespit edilmiştir. Modelin çıktısı "Normal" ise kullanıcıya sonuç ve güven yüzdesi değeri sunulmuştur eğer modelin çıktısı "Hasta" ise segmentasyon modelinin çıktısı başka bir sınıflandırma modeline verilmiştir. Bu sınıflandırma modeli de DeiT ve BeiT kullanılarak yazılmıştır ve verilen görüntüdeki dişi "Hafif Seviyede Hasta", "Orta Seviyede Hasta" ve "Şiddetli Seviyede Hasta" olmak üzere üç sınıfta sınıflandırıp grafik arayüz aracılığıyla kullanıcıya sınıflandırma modeli çıktısı ve güven yüzdesi değeri sunulmuştur.**

Anahtar Kelimeler—Ektopik Erupsiyon, Mask R-CNN, DeiT, BeiT, Sınıflandırma, Segmentasyon

Abstract—**Ectopic eruption is the eruption of teeth in an abnormal position in the mouth, deviating from the normal tooth position. This condition is usually seen in the molars of the maxilla. These teeth are deciduous teeth numbered 55 and 65 and permanent molars numbered 16 and 26. In the mandibular, ectopic eruption is rarely seen in deciduous teeth numbered 75 and 85 and permanent molars numbered 36 and 46. In children, early detection of whether the permanent molar coming out from under the deciduous molar causes ectopic eruption is important for the treatment to be applied. In this project, an application has been developed using deep learning methods to detect whether ectopic eruption is seen in these teeth together with its severity and present it to the user's information. The application is planned to be used by physicians in a clinical environment. First, the molars in the radiography image were cropped using the Mask R-CNN model. Then, these molars, which were detected and cropped in binary groups (molar and adjacent deciduous tooth), were given to the binary classification model developed using DeiT and BeiT. The binary classification model was used to determine whether the given pair of teeth had ectopic eruption. If the output of the model is "Normal", the user is presented with the result and confidence percentage value. If the output of the model is "Diseased", the output of the segmentation model is given to another classification model. This classification model is also written using DeiT and BeiT and classifies the tooth in the given image into three classes as "Mild Diseased", "Moderate Diseased" and "Severe Diseased" and presents the classification model output and confidence percentage value to the user through a graphical interface.**

Keywords—Ectopic Eruption, Mask R-CNN, DeiT, BeiT, Classification, Segmentation

I. Introduction

Ectopic eruption is a type of dental anomaly that refers to the eruption of teeth in a different position in the mouth from their expected position. This usually occurs in children during the process of deciduous teeth falling out and permanent teeth erupting. Ectopic eruption can have a serious impact on oral health and overall dental health as the teeth do not erupt correctly.

Ectopic eruption is most commonly seen in the maxilla and mandibular molars. This anomaly is usually recognized during childhood, around the age of 6-7 years, when permanent teeth begin to erupt. Causes of ectopic eruption can include genetic factors, anomalies in the jaw structure, differences in tooth size and environmental influences.

Diagnosis and treatment of ectopic eruption is important because if left untreated, it can lead to tooth misalignment, damage to neighboring teeth and general problems in oral health. Although traditional methods of examination and radiographic imaging are commonly used to detect ectopic eruption, the use of artificial intelligence technologies in recent years offers significant advantages in this field.

II. Related Work

Jialing Liu et al., who studied the detection of ectopic eruption based on radiograph images using deep learning, realised the benefit of developing automated models to allow timely interventions, since detecting eruption anomalies on radiographs is experience-dependent, and carried out work in this area[1]. Automated screening systems based on deep learning are useful and promising in detecting ectopic eruption of permanent first molars in the maxilla with relatively high specificity. However, regular follow-ups are necessary to minimise the impact of possible false negative diagnoses. Patients with ectopic eruption usually present to the dentist with the complaint of delayed tooth eruption, so the first examination usually takes place at an average age of 7 years.

Before the deep learning algorithm began, input regions from the original panoramic images were cropped in a two-step procedure. First, the computer created approximately two bounding boxes near the left and right PFM (permanent first molar) in the original panoramic image. Second, the dentists manually adjusted the size and position of the bounding boxes to make sure everything was correct. The maxillary left and right PFMLer and adjacent PSMs (permanent second molars) regions were extracted from the original images, then resized to 400 $\times$ 400 pixels for recognition. Maxillary left and right regions were evaluated respectively. In image classification based on deep learning, the features of an image are extracted with gradual convolutional layers. For this study, a wide age range of 4-9 years was selected so that as many EE symptoms as possible were covered. Finally, 1580 images were included in the study, of which 1480 images (2960 regions) were divided into a training set and 100 images (200 regions) into a test set. Finally, the fusion model was able to detect EE with an F1-Score of 0.8824. However, the false positive probability was 0.1% and the false negative probability was 0.1

In the study by Haihua Zhu et al., the importance of using artificial intelligence in the diagnosis phase is mentioned due to the difficulty of early diagnosis of ectopic eruption [2]. For the model trained in the study, 285 panoramic radiography images from 8254 children aged between 5 and 13 were selected and 438 regions were obtained from these radiographs. All were converted to the same format, resolution and grayscale before being used for nnu-net. The 220 panoramic images containing 347 ectopic eruptions of the first permanent molar were randomly selected for the training set and the rest were reserved for testing. The study used the nnU-Net architecture, a variant of the U-Net model known for its excellent performance in semantic segmentation. The model is automatically configured according to dataset characteristics to optimize its weights. The images used to train the model were manually segmented by pediatric dentists, but due to differences in manual segmentation between dentists, the largest intersections of the annotations were taken. Each pixel of the input panoramic image was assigned a class label. The network is trained by inputting images and corresponding segmentation maps in small batches. The nnU-Net model used a pre-trained U-Net architecture and was trained for 100 iterations with a dynamic learning rate. Initially, the learning rate was set at 0.01 and gradually decreased throughout the training process. To analyze the performance of the NnU-net model, four parameters were studied: IoU, precision, accuracy and F1-Score. ICCs were applied to evaluate the reliability of different dentists and McNemar chi-square test was applied to evaluate the comparison of the nnU-net model with dentists. In the McNemar test it was shown that the nnU-net model is significant and superior to the doctors.

The model achieved impressive performance metrics with an Intersection Over Union (IoU) of 0.834, indicating good consistency between the segmentation results and the annotation range. The precision of 0.845 indicates the model's ability to accurately predict Ectopic Eruption of the first permanent molar (EMM). The F1 score of 0.902 further highlights the model's superior performance in detecting EMMs. Finally, the high accuracy of 0.990 indicates the model's strong diagnostic ability to correctly identify EMMs. The designed system outperformed all 3 physicians in metrics such as IoU, precision, F1-Score, accuracy.

III. Material Methods

A. Dataset Information

The dataset to be used in the study was provided by Faculty of Dentistry of Ordu University. There are 876 panoramic radiography images in the dataset. A sample radiography image is shown in Figure 1. The training and validation of the models in this project will be carried out over 876 images in the relevant dataset.

Figure 1 Sample Radiography Image

As can be seen in Figure 2 and Figure 3, the teeth with severe ectopic eruption are generally teeth numbered 55 and 65. These teeth are molars in the maxilla. Based on this, it can be interpreted that ectopic eruption cases are more common in the maxilla than in the mandibular.

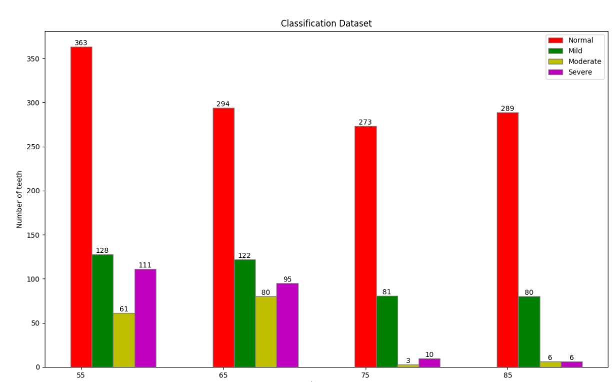

Figure 2 Distribution of Classification Dataset

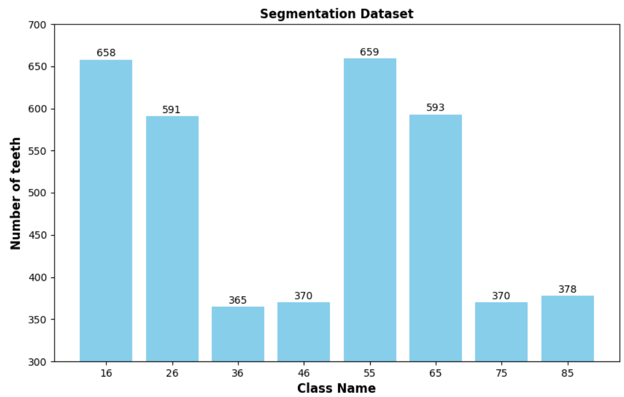

Figure 3 Json Data Distribution of Drawn Polygons

B. *Proposal Approach*

The system to be developed should take a radiography image as input and give the result of classification of 4 classes as normal, mildly ill, moderately ill and severely ill as output.

The first thing to do here is to train a segmentation model. The aim of this segmentation model is to draw the polygons of only the deciduous molars numbered 55, 65 and permanent molars numbered 16, 26 in the maxilla and the deciduous molars numbered 75, 85 and permanent molars numbered 36, 46 in the mandibular from a given radiograph image.

After the 1st and 2nd molars are detected by segmentation, the classification model will be run on these images, which teeth of this patient have ectopic eruption will be determined and they will be classified as normal, moderately trapezoidal and very trapezoidal.

1) Segmentation Model: An individual segmentation algorithm is needed to extract the relevant molars from the radiography image. Therefore, at this stage, Mask R-CNN, an Instance Segmentation algorithm, will be used to mask the teeth. An example input output diagram for the Mask R-CNN model is given in Figure 4 and examples of input and output are given in Figure 5.

Figure 4 Segmentation Model System Design

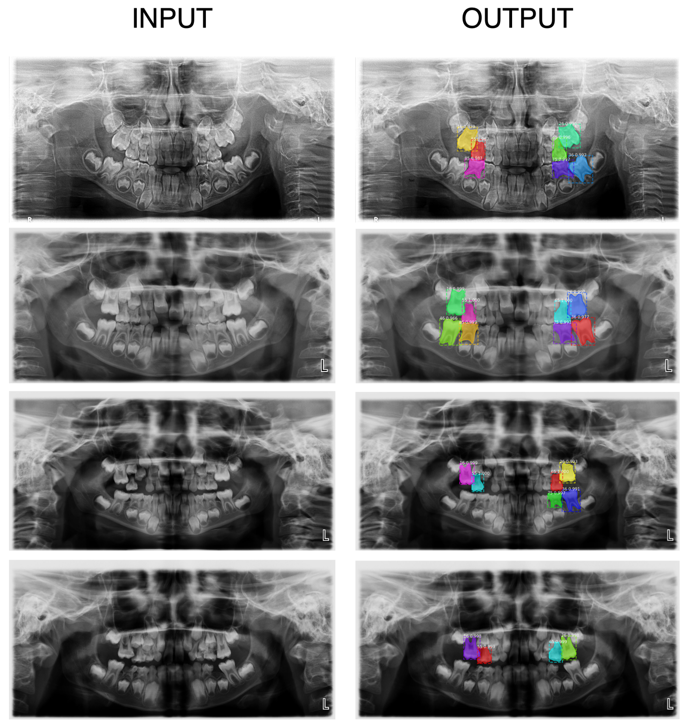

Figure 5 Example Input Output

2) Classification Model: After successfully obtaining the teeth by segmentation, it is necessary to classify them one by one. Data Efficient Image Transformer (DeiT) or BERT Pre-Training of Image Transformers (BeiT) algorithms will be used for classification. The flow of use of the models is given in Figure 6.

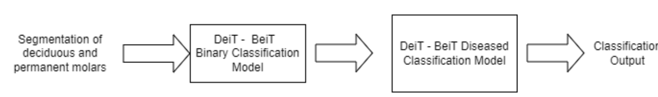

Figure 6 Classification Model System Design

IV. EXPERIMENTAL RESULTS

A. *Segmentation Model*

As can be seen in Figure 7, the model works quite successfully in detecting the teeth that are present. Looking at the last column of the figure, it can be seen that the model also finds some unlabeled teeth in the dataset. One of the reasons for this is that some of the teeth in the dataset are present but not labeled. Therefore, the percentage values in the last column may be misleading in measuring the success of the model. The percentile values in the bottom row give more information about the success of the model than the percentile values in the last column. Looking at the bottom row, it is observed that the model gives a more successful result for teeth 16, 26, 55, 65 than for teeth 36, 46, 75, 85 because there is more data in the maxilla compared to the mandibular.

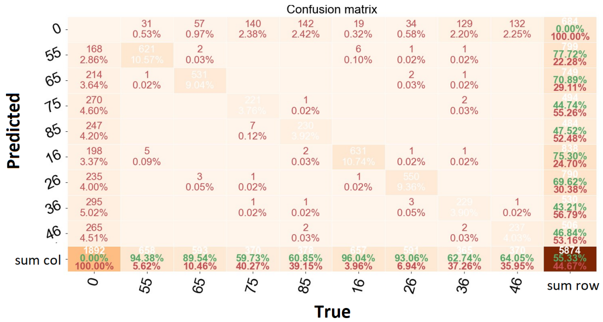

Figure 7 Confusion Matrix of 5-Fold Segmentation Model

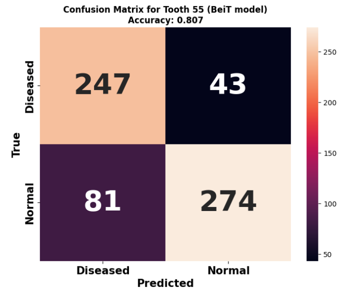

Figure 8 Best Confusion Matrix of Tooth 55

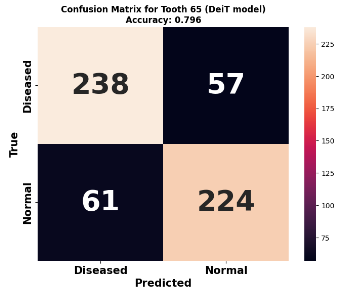

Figure 9 Best Confusion Matrix of Tooth 65

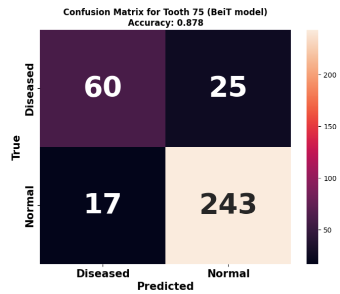

Figure 10 Best Confusion Matrix of Tooth 75

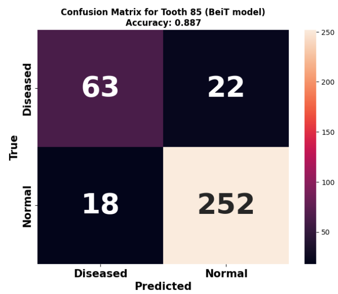

Figure 11 Best Confusion Matrix of Tooth 85

B. Classification Model

Table 1 shows the performance of the classification models used to classify the segmented teeth. It can be observed that the DeiT and BeiT models perform approximately similarly. The models are quite successful in binary classification, that is, determining whether the tooth in the image is diseased or normal. When it comes to disease classification, as can be seen in Figure 2, the models do not work very well due to the insufficient number of diseased teeth in the dataset. For teeth 75 and 85, the model seems to be successful, but this is due to the fact that teeth 75 and 85, which are marked as diseased in the dataset, are not evenly distributed and most of them are mildly diseased.

			Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Ortalama
BeiT	**İkili Sınıflandırma**	55	0.88	0.82	0.78	0.81	0.75	**0.81**
		65	0.79	0.69	0.78	0.78	0.76	**0.76**
		75	0.87	0.83	0.91	0.86	0.93	**0.88**
		85	0.93	0.92	0.87	0.83	0.89	**0.89**
	Hastalık Sınıflandırması	55	0.33	0.44	0.39	0.35	0.47	**0.40**
		65	0.36	0.31	0.31	0.36	0.19	**0.33**
		75	0.88	0.88	0.94	0.94	0.94	**0.92**
		85	0.88	0.88	0.88	0.69	0.81	**0.83**
DeiT	**İkili Sınıflandırma**	55	0.88	0.73	0.78	0.77	0.78	**0.79**
		65	0.81	0.79	0.81	0.87	0.70	**0.80**
		75	0.72	0.75	0.91	0.84	0.87	**0.82**
		85	0.89	0.83	0.83	0.85	0.90	**0.86**
	Hastalık Sınıflandırması	55	0.42	0.35	0.39	0.32	0.35	**0.37**
		65	0.31	0.38	0.24	0.33	0.33	**0.32**
		75	0.94	0.94	0.94	0.94	0.94	**0.94**
		85	0.81	0.75	0.88	0.88	0.88	**0.84**

Table 1 Performance comparison of classification models

V. Discussion

A. BeiT and Deit Binary Classification Model

For the teeth in the maxilla, the model learned the diseased examples better because the distribution of the dataset of teeth located in maxilla shown in Figure 8 and Figure 9 is more uniform than the distribution of the dataset of the teeth located in mandibular shown in Figure 10 and Figure 11. Also the dataset of teeth in the mandibular does not have a sufficient amount of diseased examples. A very high proportion of the samples are normal and therefore the model is biased.

B. BeiT and DeiT Diseased Classification Model

When Figure 12 and Figure 13 are examined, it is seen that the models cannot achieve as much success in diseased classification as in binary classification. One of the main reasons for this is the closeness between classes. The difference between classes in binary classification is clearer than the difference between classes in diseased classification. Also, since only diseased teeth are used for diseased classification, the dataset becomes significantly smaller. This is also true for the mandibular teeth 75 and 85 in Figure 14 and Figure 15, but since ectopic eruption is generally not seen in the mandibular, and when it is seen, it is seen mildly diseased, almost all of the dataset here consists of mildly diseased examples. Therefore, the models here work almost like a single-class classification problem. So, their success seems to be high.

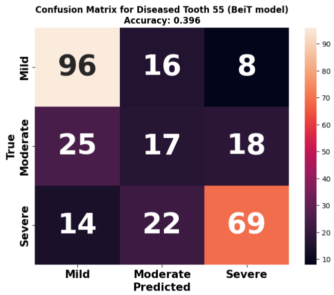

Figure 12 Best Confusion Matrix of Diseased Tooth 55

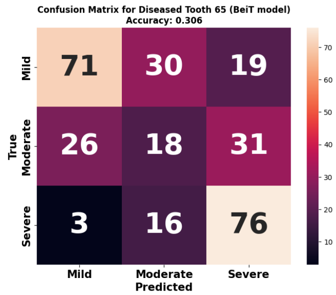

Figure 13 Best Confusion Matrix of Diseased Tooth 65

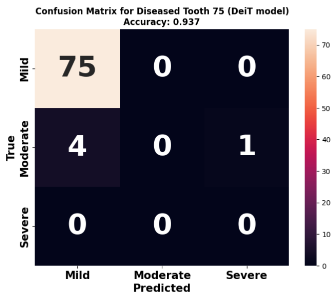

Figure 14 Best Confusion Matrix of Diseased Tooth 75

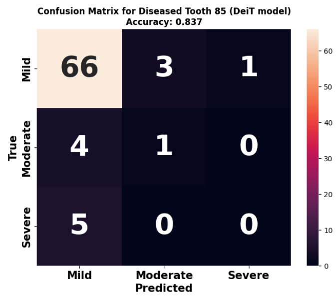

Figure 15 Best Confusion Matrix of Diseased Tooth 85

VI. Conclusion

In conclusion, in this project, ectopic eruption detection was highly successful by detecting deciduous and permanent molars from radiographs using the Mask R-CNN model and cropping the relevant area of the image and feeding it to the classification models (DeiT, BeiT).

There was no significant difference between the DeiT and BeiT models and both models performed adequately. The first classification model, the 'Normal' and 'Diseased' classification model, achieved a higher success rate than the second model, the 'Mild', 'Moderate' and 'Severe' classification model. This is due to the distribution and size of the dataset used. While the first model used all data, the second model used data except for the 'Normal' class. This resulted in a smaller dataset for the second model. In addition, since the number of data belonging to the teeth in the maxilla is higher than the teeth in the mandibular, the success obtained in the maxilla is higher.

References

[1] J. Liu, Y. Liu, S. Li, S. Ying, L. Zheng, and Z. Zhao, "Artificial intelligence-aided detection of ectopic eruption of maxillary first molars based on panoramic radiographs," *J. Dent.*, vol. 125, no. 104239, p. 104239, Oct. 2022.

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