

## ORIGINAL RESEARCH ARTICLE

# Automatic Detection of Dentigerous Cysts on Panoramic Radiographs: A Deep Learning Study

Gürkan Ünsal <sup>1,2,\*</sup>, Ece Of <sup>3</sup>, İrem Türkan <sup>3</sup>, İbrahim Şevki Bayraktar <sup>4</sup> and Özer Çelik <sup>5</sup>

<sup>1</sup>Near East University, Faculty of Dentistry, Department of Dentomaxillofacial Radiology, Cyprus and <sup>2</sup>Near East University, DESAM Institute, Cyprus and <sup>3</sup>Near East University, Faculty of Dentistry, Cyprus and <sup>4</sup>Department of Dentomaxillofacial Radiology, Eskişehir Osmangazi University, Faculty of Dentistry, Eskişehir, Turkey and <sup>5</sup>Department of Mathematics-Computer, Eskişehir Osmangazi University, Faculty of Science, Eskişehir, Turkey

\*Corresponding Author; gurkanunsal@aol.com

## Abstract

**Purpose:** The aim of this study is to create a model that enables the detection of dentigerous cysts on panoramic radiographs in order to enable dentistry students to meet and apply artificial intelligence applications.

**Materials & Methods:** E.O. and I.T. who are 5th-year students of the faculty of dentistry, detected 36 orthopantomographs whose histopathological examinations were determined as Dentigerous Cyst, and the affected teeth and cystic cavities were segmented using CranioCatch's artificial intelligence supported clinical decision support system software. Since the sizes of the images in the data set are different from each other, all images were resized as 1024x514 and augmented as vertical flip, horizontal flip and both flips were applied on the train-validation. Within the obtained data set, 200 epochs were trained with PyTorch U-Net with a learning rate of 0.001, train: 112 images (112 labels), val: 16 images (16 labels). With the model created after the segmentations were completed, new dentigerous cyst orthopantomographs were tested and the success of the model was evaluated.

**Results:** With the model created for the detection of dentigerous cysts, the F1 score ( $2TP / (2TP+FP+FN)$ ) precision ( $TP / (TP+N)$ ) and sensitivity ( $TP / (TP+FN)$ ) were found to be 0.67, 0.5 and 1, respectively.

**Conclusion:** With a CNN approach for the analysis of dentigerous cyst images, the precision has been found to be 0.5 even in a small database. These methods can be improved, and new graduate dentists can gain both experience and save time in the diagnosis of cystic lesions with radiographs.

**Key words:** artificial intelligence; dentigerous cyst; deep learning

## Introduction

Odontogenic cysts and benign odontogenic tumours of the jaws are usually painless and asymptomatic unless they grow large enough to cover the entire jawbone, cause significant swelling, or weaken it to cause pathological fractures. Most of these lesions can be identified at an earlier stage with a routine radiographic examination called an orthopantomogram. Although cystic lesions are often defined as incidental findings on orthopantomograms without any obvious symptoms, regardless of the patient's main complaint, radiographic interpretation training and experience are required for an accurate diagnosis. <sup>1-4</sup> Convolutional Neural Networks (CNN) are gaining increasing attention in the field of medical imaging to assist clinicians in their diagnosis or to obtain opinions to confirm their diagnoses. U-Net, one of these deep learning tools that can

detect and classify images, has been developed for segmentation in medical image processing studies. <sup>5-7</sup> The aim of this study is to create a model that enables the detection of dentigerous cysts on orthopantomographs in order to enable dentistry students to meet and apply artificial intelligence applications.

## Materials and Methods

E.O. and I.T., two 5th class dentistry students, scanned the database of Near East University, Faculty of Dentistry, Department of Dentomaxillofacial Radiology in order to detect OPGs with dentigerous cysts. G.U. supervised and confirmed the dentigerous cysts with their radiographic features. OPGs with motion artefact and cases without any histopathological examination were excluded from the



Figure 1. A dentigerous cyst that is attached to the cementoenamel junction of a mandibular left third molar was successfully detected by the model

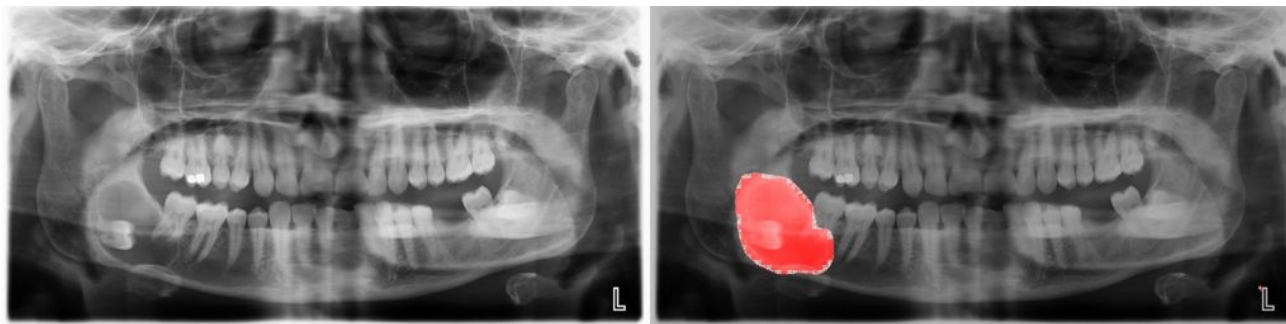


Figure 2. A dentigerous cyst that is attached to the cementoenamel junction of a horizontally impacted mandibular right third molar was successfully detected by the model

study. A total of 36 dentigerous cyst cases were found and OPGs of those cases were uploaded to the database of CranioCatch's artificial intelligence supported clinical decision support system software following the data anonymization. The cystic cavities and the affected teeth were segmented by E.O. and I.T. with the supervision of G.U.

I.S.B. and O.C. resized all images as 1024x514 since those images had different sizes and were obtained from different OPG units. They also applied vertical flip, horizontal flip and both flips on the train-validation for augmentation. Within the obtained dataset, 200 epochs were trained with PyTorch U-Net with a learning rate of 0.001, train:112 images (112 labels), val:16 images (16 labels). After the creation of the model by I.S.B. and O.C. new dentigerous cyst OPGs were uploaded as test data and the success of the model was evaluated.

The study was performed in accordance with the tenets of the 1964 Helsinki Declaration and its later amendments. Due to the retrospective nature of this study and anonymization of the images, it was granted an exemption in writing by the Near East University IRB

## Results

With the model created for the detection of dentigerous cysts, the accuracy ( $2TP / (2TP+FP+FN)$ ) precision ( $TP / (TP+N)$ ) and sensitivity ( $TP / (TP+FN)$ ) were found to be 0.67, 0.5 and 1, respectively. 3 successful detection examples were given in (Figure 1-3).

## Discussion

Our main aim was to show the effects and possibilities of deep learning algorithms to our 5th-year students. Since we planned a pilot study for our students, we had some limitations in our study. More dentigerous cysts could have been scanned and segmented in order to increase the sensitivity and dice score of our algorithm; however, such a study would require a bigger or public database which is not accessible in the Turkish Republic of Northern Cyprus. Moreover,

we did not include any data without histopathological examination to maintain the "ground truth"; thus, we excluded 21 cases that had the characteristic radiographic findings of dentigerous cysts.

Most of the artificial intelligence studies in dentistry nowadays are regarding dentomaxillofacial radiology and several companies made investments in order to apply AI in radiological diagnosis.<sup>5-10</sup> Since most of the data which are used in testing are private and confidential, the lack of public datasets may still remain a challenge.<sup>8,11,12</sup> Another problem is only a few studies have around 1000 samples in both test and control groups with less than 90% of diagnostic accuracy. Both the diagnostic accuracy and sample size falls short since any score lower than 90% is not desirable. Increasing the sample size is crucial in order to achieve this goal.<sup>8,13-16</sup>

To the best of our knowledge, there are only 6 deep learning studies regarding the odontogenic cysts in the literature. First was conducted by Poedjiastoeti et al.<sup>17</sup> in 2018 in which they created a CNN model for ameloblastoma and odontogenic keratocyst detection. However, instead of using the 2017 WHO classification, the authors mentioned the odontogenic keratocysts as keratocystic odontogenic tumours. They also compared the CNN model's sensitivity, specificity, accuracy and diagnostic time with the oral and maxillofacial specialists' and their results were "0.818, 0.833, 0.830, and 38 seconds" for the CNN model and "0.811, 0.832, 0.829, and 23.1 minutes" for the specialists, respectively. Lee et al.<sup>18</sup> conducted a study in order to evaluate the diagnosis and detection of 3 three different types of odontogenic cysts (dentigerous cysts, odontogenic keratocyst, periapical cyst) with OPG and CBCT. They used GoogLeNet Inception-3 architecture and evaluated the area under the ROC curve (AUC), sensitivity, specificity. Their pre-trained model had a 0.914 AUC value, 0.961 sensitivity and 0.771 specificity in CBCT images. Ariji et al.<sup>19</sup> conducted a similar study to test if deep learning object detection can also detect and classify lytic lesions on OPGs. They included lesions that are 10mm or greater and localized in the mandible. A learning model was created with DetectNet for "ameloblastoma, odontogenic keratocyst, dentigerous cyst, radicular cyst and simple bone cavities". They found that the best combination of classification and detection has occurred with dentigerous cysts and the sensitivity of the study was 0.88. Yang

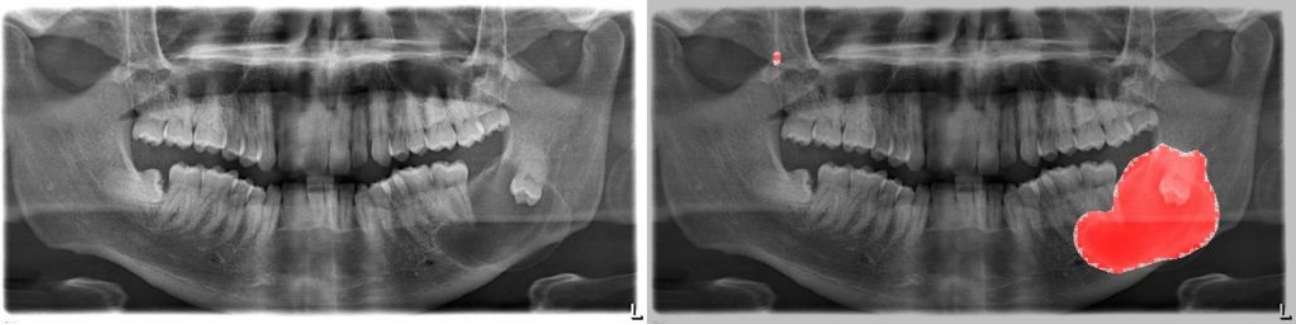


Figure 3. A dentigerous cyst that is attached to the cementoenamel junction of an inverted impacted mandibular left third molar was successfully detected by the model

Table 1. Publications' sensitivity, specificity, precision, accuracy, AUC and diagnostic time regarding the deep learning studies about the detection and classification of odontogenic lesions

Authors	Year	Lesions	Sensitivity (Recall)	Specificity	Precision	Accuracy	AUC	Diagnostic Time
Poedjastoeti et al	2018	Odontogenic Keratocyst and Ameloblastoma	0,818	0,833	x	0,83	x	38 seconds
Lee et al	2019	Dentigerous cyst, odontogenic keratocyst, periapical cyst	0,961	0,771	x	x	0,914	x
Ariji et al	2019	Dentigerous cyst, odontogenic keratocyst, radicular cyst, ameloblastoma, simple bone cyst	0,88	x	x	x	x	x
Yang et al	2020	Dentigerous cysts, Odontogenic keratocyst, Ameloblastoma	0,68	x	0,707	x	x	x
Kwon et al	2020	Dentigerous Cyst, Periapical Cyst, Odontogenic Keratocyst, Ameloblastoma	0,889	0,972	x	0,956	0,94	x
Liu et al	2020	Odontogenic Keratocyst and Ameloblastoma	0,928	0,878	x	0,9036	0,946	x

et al.<sup>20</sup> conducted a study with real-time object detecting deep CNN YOLO v2 which can both detect and classify an object on OPGs. They labelled the lesions as odontogenic keratocyst, ameloblastoma, dentigerous cyst and no cyst. Their model has a 0.707 precision value and 0.680 recall value. Kwon et al.<sup>21</sup> conducted a study also with the CNN YOLO's newer version v3 for the dentigerous cyst, periapical cyst, odontogenic keratocyst and ameloblastoma detection and classification. Their augmented data set had 0.889 sensitivity, 0.972 specificity, 0.956 accuracy and 0.94 AUC value. Liu et al.<sup>22</sup> focused on the differential diagnosis between the ameloblastoma and odontogenic keratocyst since it affects the surgical approach. They provided a CNN model which is based on transfer learning and they achieved 0.9036 accuracy, 0.946 AUC, 0.9288 sensitivity and 0.878 specificity values. They also used 3 other networks (VGG-19 and ResNet-50, another network trained from scratch) and achieved 0.8072, 0.7831 and 0.6988 accuracy values, respectively.

Panoramic radiograph is the most used imaging in dentistry; however, to achieve acceptable diagnosis accuracy with AI, higher standardization protocols must be applied in order to avoid any failure due to image quality, patient positioning and magnification. Radiographs that were taken with different orthopantomography devices should be evaluated together to ensure a reliable data set construction. A common mistake with the current studies is collecting data from a single radiography device which will cause a

problem since different models are created for each machine and it is likely that a model for a device will not apply to other machines. Manually cropped radiographs with the region of interest is also another challenge since the newly-developed software will be unable to interpret the whole image.

## Conclusion

With a CNN approach for the analysis of dentigerous cyst images, the accuracy, precision and sensitivity were found 0.67, 0.5 and 1 even in such a small dataset. These methods can be improved, and new graduate dentists can gain both experience and save time in the diagnosis of cystic lesions with radiographs.

## Acknowledgements

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## Author Contributions

E.O. and I.T. scanned the database in order to detect OPGs with dentigerous cysts. G.U. supervised and confirmed the dentigerous cysts with their radiographic features. The cystic cavities and the affected teeth were segmented by E.O. and I.T. with the supervision of G.U., I.S.B. and O.Ç. resized all images. I.S.B. and O.C. created and evaluated the model.

## Conflict of Interest

Authors declare that they have no conflict of interest.

## Authors' ORCID(s)

G.U. [0000-0001-7832-4249](https://orcid.org/0000-0001-7832-4249)  
 E.O. [0000-0001-7687-9750](https://orcid.org/0000-0001-7687-9750)  
 I.T. [0000-0002-4546-0161](https://orcid.org/0000-0002-4546-0161)  
 I.S.B. [0000-0001-5036-9867](https://orcid.org/0000-0001-5036-9867)  
 O.C. [0000-0002-4409-3101](https://orcid.org/0000-0002-4409-3101)

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