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ORIGINAL ARTICLE

Deep-learning approach for caries detection and segmentation on dental bitewing radiographs

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Abstract

Objectives The aim of this study is to recommend an automatic caries detection and segmentation model based on the Convolutional Neural Network (CNN) algorithms in dental bitewing radiographs using VGG-16 and U-Net architecture and evaluate the clinical performance of the model comparing to human observer.

Methods A total of 621 anonymized bitewing radiographs were used to progress the Artificial Intelligence (AI) system (CranioCatch, Eskisehir, Turkey) for the detection and segmentation of caries lesions. The radiographs were obtained from the Radiology Archive of the Department of Oral and Maxillofacial Radiology of the Faculty of Dentistry of Ordu University. VGG-16 and U-Net implemented with PyTorch models were used for the detection and segmentation of caries lesions, respectively.

Results The sensitivity, precision, and F-measure rates for caries detection and caries segmentation were 0.84, 0.81; 0.84, 0.86; and 0.84, 0.84, respectively. Comparing to 5 different experienced observers and AI models on external radiographic dataset, AI models showed superiority to assistant specialists.

Conclusion CNN-based AI algorithms can have the potential to detect and segmentation of dental caries accurately and effectively in bitewing radiographs. AI algorithms based on the deep-learning method have the potential to assist clinicians in routine clinical practice for quickly and reliably detecting the tooth caries. The use of these algorithms in clinical practice can provide to important benefit to physicians as a clinical decision support system in dentistry.

Keywords Artificial intelligence · Deep learning · Tooth caries · Bitewing radiographs · Dentistry

Introduction

Dental caries is a chronic infectious disease that affects about one in two people around the world [1]. Treatment planning needs early and accurate diagnosis of caries. To detect dental caries, fluorescence camera, laser fluorescence devices, fiber-optic transillumination, quantitative light-induced fluorescence, LED technology, digital imaging, electrical caries monitor can be used. But the method widely used in the clinic based on a combination of visual-tactile and radiographic examination [2]. Radiological examination has an important place in dentistry practice. Panoramic, periapical, and bitewing films are routinely used to examine dental caries and other diseases. Generally bitewing images have been used for the detection proximal dental caries lesions depth, which are invisible or poorly visible for inspection. Carefully interpretation of radiographs is significant for the detection and treatment procedures of the dental caries. But diagnostic accuracy of approximal caries lesions depends on education level and experience of dentists [3]. After using digital images in dentistry, computer-aided diagnosis (CAD) systems have been developed to assist the clinicians for improve and faster decision on diagnosis and, moreover, treatment. Today classical engineering methods have been replaced by artificial intelligence (AI) studies. Especially, convolutional neural networks (CNNs) are the most widespread deep-learning (DL) model types in medical and dental imaging at the present time [4]. In the literature, many different conditions and clinical problems such as tooth detection, numbering and segmentation [5–10], periodontal bone loss detection [11–13], caries detection and segmentation [14–19], periapical lesion detection [20–22], evaluation of

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Extended author information available on the last page of the article the tooth morphology [23, 24], root fracture [25], impacted teeth and mandibular canal detection [26–29], detection of jaw lesions [30–34], implant detection and classification [35, 36], osteoporosis detection [37], evaluation of the maxillary sinus [38, 39], cephalometric landmark detection and analysis [40, 41], automatic pharyngeal airway detection [42], etc. were evaluated using CNN-based algorithm in dentistry.

The aim of the study is to propose an automatic caries detection and segmentation system based on the CNN algorithms in dental bitewing radiographs using VGG-16 and U-Net architecture and evaluate clinical performance of the neural networks comparing to human observer.

Materials and methods

Study design

In the retrospective study, automatic caries detection and segmentation models (CranioCatch, Eskisehir, Turkey) in dental bitewing radiographs using VGG-16 and U-Net architecture were created. Ordu University Non-interventional Clinical Research Ethics Board (decision date, meeting number and decision number: 27.02.2020/05/26) was authorized the study protocol. The principles of the Helsinki Declaration were followed in the study. Checklist for Artificial Intelligence in Medical Imaging (CLAIM) and Standards for the Reporting of Diagnostic Accuracy Studies (STARD) Checklist were used for preparing the manuscript.

Data sources

Dental bitewing radiographs obtained from individuals over the age of 18 were included in the study. Gender differences were not considered. Dental bitewing radiographs were obtained from the radiology archive of the Department of Dento-Maxillofacial Radiology of Ordu University School of Dentistry. A power analysis was conducted using PASS Power Analysis and Sample Size software (Version 15.0.5, NCSS, Kaysville, Utah, USA) that present detection and segmentation of dental caries on bitewing radiographs could be obtained at least with 152 radiographs at a power of 0.95 (alpha = 0.05). The dataset included 613 anonymized bitewing radiographs with no artefacts from adults obtained from January 2018 to January 2020. Bitewing radiographs were obtained with the Kodak CS 2200 (Carestream Dental, Atlanta, GA) periapical dental imaging equipment. 2 different phosphor plate systems (Carestream CS 7600, Carestream Dental, Atlanta, GA and Kodak CR, Carestream Dental, Atlanta, GA) with the following parameters 50 kVp, 5 mA, 0.1 s were used to image acquisition.

Ground truth

An oral and maxillofacial radiology expert (Y.Y.) with 9 years and a specialist of restorative dentistry (S.A.) with 9 years' experience provided ground truth annotations for the dental bitewing images using CranioCatch Labeling Tool (Eskisehir, Turkey) with the agreement for each label. Experts were asked to draw polygonal boxes around all caries lesions on dental bitewing radiographs.

Models

Detection model

Pre-processing steps

621 anonymized mixed size dental bitewing images were resized 512 × 512, and 2325 images were obtained by applying augmentation (horizontal and vertical flip and both). Then dataset was divided as train, validation, and test group.

Training group: 2072 (5779 labels).

Validation group: 200 (392 labels).

Test group: 53 (168 labels).

Deep-convolutional neural network (CNN) architecture

VGG is a CNN architecture presented as "Very deep convolutional networks for large-scale image recognition.'' by K. Simonyan and A. Zisserman in the 2014 [43]. VGG-16 is a version of VGG network with 16 convolution layers. VGG-16 contains 16 convolutional layers, and it is so attractive due to its consistent structure. Various 3 × 3 convolutional and 2 × 2 pooling layers were integrated over and over. VGG-16 has an exceptional success in image classification because of the unusual characteristic derivation's ability. Follow the convolutional layers, there are three fully connected layers. The soft-max layer is the last layer of architecture [43].

Training

Python, an open-source programming language (version 3.6.1; Python Software Foundation, Wilmington, DE, USA) was used to develop AI algorithm. PyTorch library was used for creating of AI algorithm with VGG-16 network. The training method was applied using computer equipment of Ordu University Faculty of Dentistry Dental-AI Laboratory including Dell PowerEdge T640 Calculation Server (Dell Inc., Texas, USA), Dell PowerEdge T640 GPU Calculation Server (Dell Inc., Texas, USA), Dell PowerEdge

R540 Storage Server (Dell Inc., Texas, USA). Details of equipment features are provided in the appendix. The caries detection model with VGG-16 implemented with PyTorch was trained with 200 epochs. An AI model (CranioCatch, Eskisehir, Turkey) was created to automatically detect of caries lesions on dental bitewing radiographs (Fig. 1).

Segmentation model

621 anonymized mixed size dental bitewing images were resized to 512 × 512. Contrast limited adaptive histogram equalization (CLAHE) was applied in all images to make more visible of caries lesion. Blank images were generated and made masks from labels. 2292 images were obtained by applying augmentation (horizontal and vertical flip and both) on training and validation dataset. Then data were split into again train, validation, and test group, both normal and mask images.

Training group: 1968 (8080 labels).
Training-mask group: 1968 (8080 labels).
Validation group: 260 (1892 labels).
Validation-mask group: 260 (1892 labels).
Test group: 64 (151 labels).
Test-mask group: 64 (151 labels).

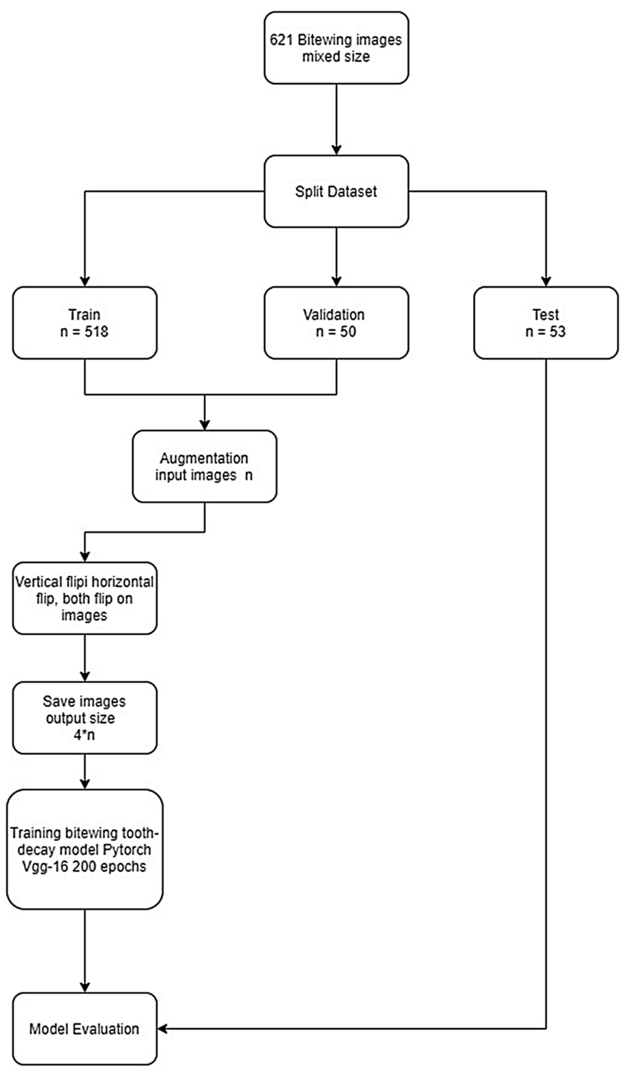

Fig. 1 Diagram of the caries detection model development steps

Deep-convolutional neural network (CNN) architecture

The U-Net architecture has four block levels containing two convolutional layers with batch normalization and a Rectified Linear Unit Activation function (ReLu). There is a maximum pool layer in the encoding section and up-convolution layers in the decoding section. Each block has 32, 64, 128, or 256 convolutional filters. Besides the bottleneck, the layer comprises 512 convolutional filters. Skip connections to the corresponding layers from the encoding layers are present in the decoding part [44].

Training

Python, an open-source programming language (version 3.6.1; Python Software Foundation, Wilmington, DE, USA) was used to develop AI algorithm. PyTorch library was used for creating of AI algorithm with U-Net network. The training method was applied using computer equipment of Eskisehir Osmangazi University Faculty of Dentistry Dental-AI Laboratory including Dell PowerEdge T640 Calculation Server (Dell Inc., Texas, USA), Dell PowerEdge T640 GPU Calculation Server (Dell Inc., Texas, USA), Dell PowerEdge R540 Storage Server (Dell Inc., Texas, USA). Details of equipment features are provided in the appendix. The caries segmentation model with Pytorch U-Net was trained with 100 epochs and the best model 87th epoch was recorded. An AI model (CranioCatch, Eskisehir, Turkey) was created to automatically segmentate of caries lesions on dental bitewing radiographs (Fig. 2).

Testing on external data

External radiographic dataset achieved from radiology archive of Eskisehir Osmangazi University Faculty of Dentistry Department of Dento-Maxillofacial Radiology was used to testing performance of caries detection and segmentation models. 50 dental bitewing radiographs were achieved using a ProX periapical X-ray unit (Planmeca, Helsinki, Finland) with the following parameters: 220–240 V, 60 kVp, 2 mA, and 0.05 s scan time using ProScanner Phosphor Plate and Scanning System (Planmeca, Helsinki, Finland). 2 experienced dentomaxillofacial radiologist

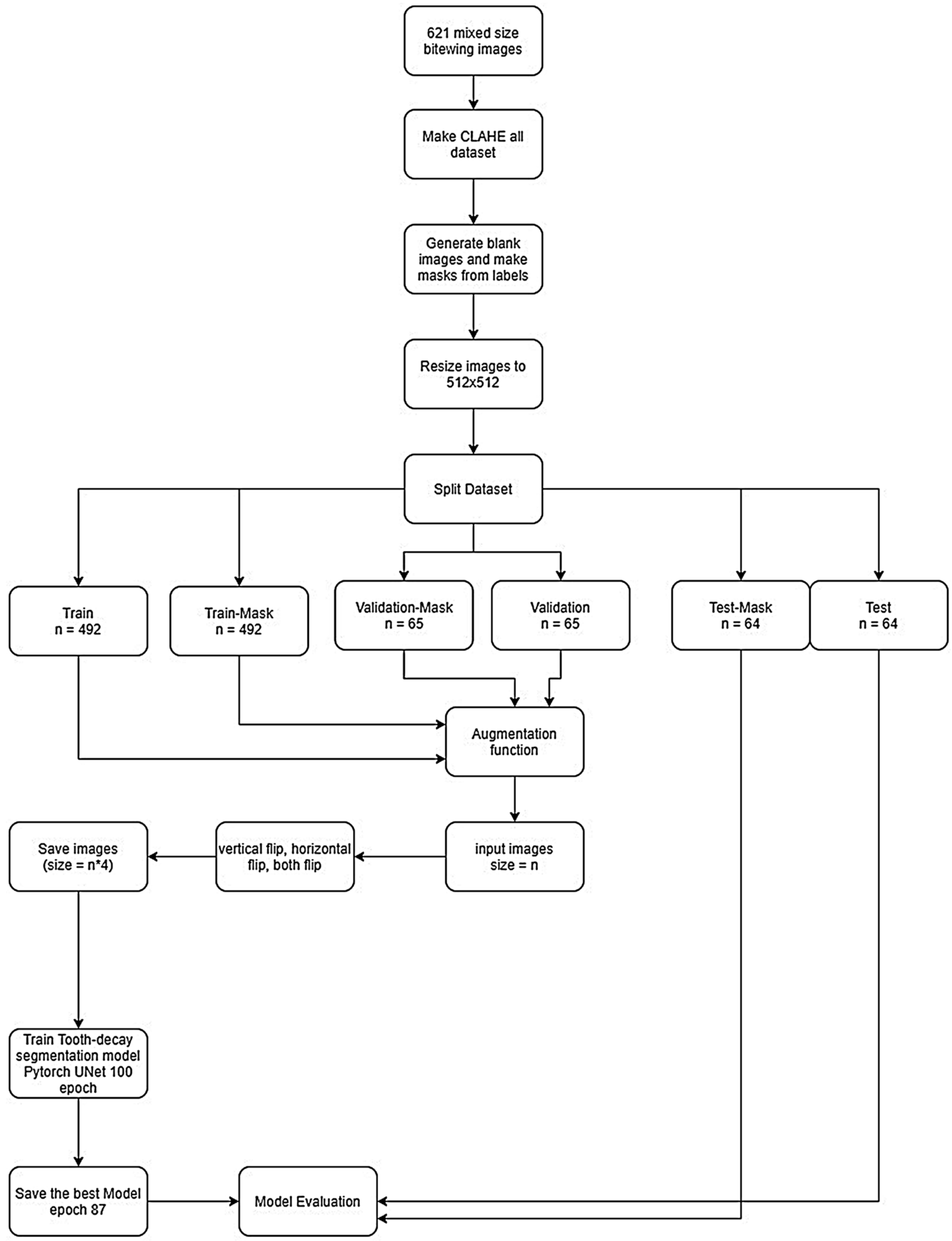

Fig. 2 Diagram of the caries segmentation model development steps

(K.O. with the 18 years' experience and I.S.B with the 10 years' experience) with the agreement each label was annotated radiographic dataset for reference standards for testing model performance on the external dataset. Also; 5 different observers with the different experience (E.B.—10 years experienced dentomaxillofacial radiologist, A.P.—10 years experienced dentomaxillofacial radiologist, S.A.—10 years experienced restorative dentistry specialist, S.A.—3 years experienced assistant-restorative dentistry specialist, H.S.—2 years experienced assistant-dentomaxillofacial radiologist) were evaluated to external datasets for the compare AI model performance.

Evaluation

Metrics of model performance

The confusion matrix was used to determine the model performance. The metrics used to assess the performance of the caries detect and segmentation model were as follows:

True positive (TP): The number of accurate detected or segmented of the caries lesion.

False positive (FP): The number of caries lesions were not detected or segmented.

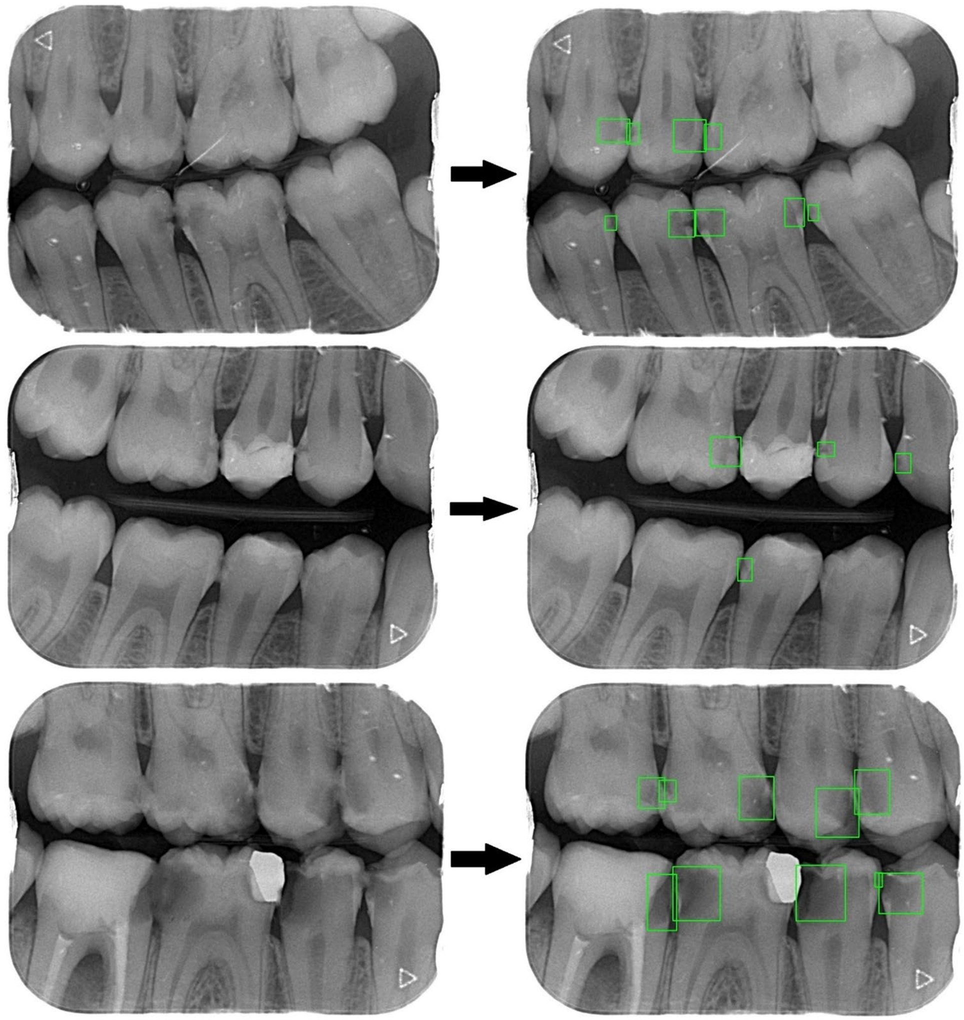

Fig. 3 Tooth caries detection on bitewing radiographs using the AI model

False negative (FN): The number of detected or segmented of caries lesion even though there was no caries lesion.

The performance metrics of the model were determined according to the formulas using number of TP, FP, and FN below.

Sensitivity (Recall, True positive rate (TPR): TP/(TP + FN).

Precision (Positive predictive value (PPV)): TP/(TP + FP).

F1 score: 2TP/(2TP + FP + FN).

Results

The AI models based on the deep-CNN architecture showed promise results for caries detection and segmentation in dental bitewing radiographs. (Fig. 3 and 4) The sensitivity, precision, and F-measure values were 0.84, 0.84, and 0.84, respectively, to caries detection. The sensitivity, precision, and F1-measure values were 0.81, 0.86, and 0.84, respectively, to caries segmentation (Table 1). Comparing to 5 different experienced observers and AI models on external radiographic dataset, AI models showed superiority to assistant specialists. Table 2 was summarized comparing to success of the AI models and observers.

Discussion

Tooth caries is one of the most prevalent diseases in society. Early and reliable detection of tooth caries ensures appropriate treatment and prevents further problems. Various diagnostic methods including near-infrared-light transillumination (NILT), digital imaging fiber-optic transillumination (DIFOTI), quantitative light-induced fluorescence (QLF), laser fluorescence, ultrasonic caries detector, optical coherence tomography (OCT), tuned aperture computed tomography (TACT), electrical conductance measurement (ECM), digital subtraction radiography (DSR) are available in clinical

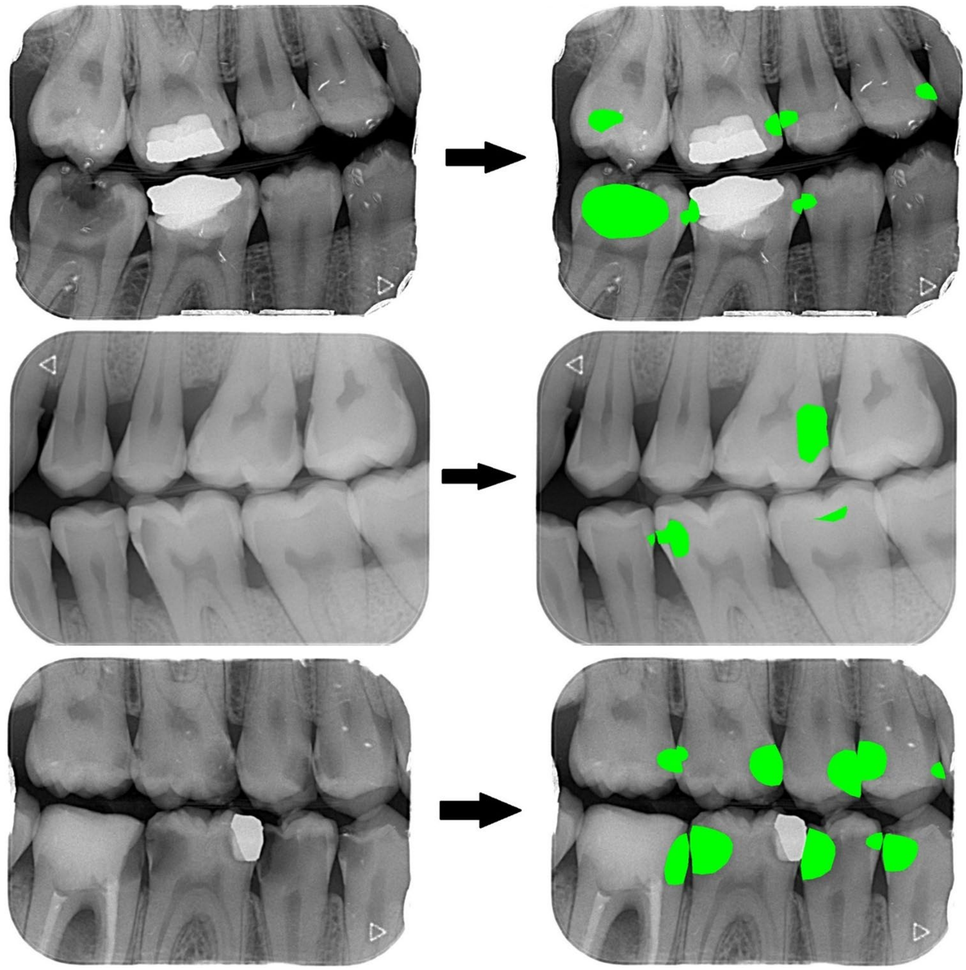

Fig. 4 Tooth caries segmentation on bitewing radiographs using the AI model

application in dentistry [45–47]. Although there are many different techniques, radiographic evaluation has a significant place in the detection of tooth decay, currently. Bitewing radiographs are even the essential diagnostic method used for the detection of tooth caries [48]. From the past to present, different image processing techniques and neural networks have used to develop the automatic caries detection system using digital images and radiographs. Geetha et al. [49] proposed the detection system includes filtering of Laplacian, adaptive threshold based on the window, morphological operations, statistical property extraction, and back-propagation neural network (BPNN) for detection of tooth caries intra-oral digital radiographs. In this caries detection system, task of the back-propagation neural network trained with tenfold cross validation was that show the presence or absence of caries as a classifier in intra-oral digital radiographs. This study results show that BPNN was classified radiographs more accurate rather than support vector machine (SVM) and K-nearest neighbors (KNN) algorithms in terms of classification of the presence or absence of caries. Accuracy, receiver operating characteristic curve (ROC) area, precision–recall curve (PRC) area values of the suggested diagnostic system were 97.1%, 0.977, and 0.987, respectively [49]. Kositbowornchai et al. [14] suggested a neural network based on learning vector quantization (LVQ) to diagnose artificial dental caries and detect depth of caries using images from a charged-coupled device (CCD) camera and intra-oral digital radiographs. The sensitivity and specificity rates of tooth caries perception by the CCD camera and digital radiographs were found as 0.77, 0.85 and 0.81, 0.93, at 95% confidence internal (CI) level, respectively. The accuracy rate of caries depth-perception by the CCD camera and digital radiography was found as 58% and 40%, respectively [14]. Recently, the increase in the use of CNN-based algorithms based on deep learning in medical image analysis and obtaining successful results from these algorithms has made the use of these algorithms widespread in caries detection. Casalegno et al. [17] presented a deep-learning model based on a CNN trained on a semantic segmentation duty for the automated perception of tooth caries in near-infrared-light transillumination (NILT) images. Although they used limited number of training data, proposed model obtained total average intersection-over-union (IOU) rate of 72.7% on a 5-grade segmentation duty and especially an IOU rate was found as 49.5% and 49.0% for interproximal and occlusal tooth caries, respectively.

Table 1 Predictive performance measurement using the AI model in internal test data (CranioCatch, Eskisehir, Turkey)

	True positive (TP)	False positive (FP)	False negative (FN)	Sensitivity	Precision	F1 score
Caries detection	144	27	27	0.84	0.84	0.84
Caries segmentation	124	20	29	0.81	0.86	0.84

Their model obtained 83.6% and 85.6% of area under the ROC rate for occlusal and interproximal tooth caries, respectively, for the classification of the presence or absence of tooth caries. Their study concluded that a DL-based solution for the evaluation of NILT images has promising results [17]. Schwendicke et al.[19] used the deep-CNN methods including Resnet18, Resnext50 to diagnose tooth caries in NILT images. The two models had similar performance of predicting caries area on tooth structure of NILT images. Resnext50 architecture was achieved the best AUC value. The mean AUC was found as 0.74 at 95% CI value. Sensitivity and specificity were found as 0.59 and 0.76, respectively [19]. Devito et al.[50] were evaluated success of the radiographic diagnosis of proximal caries using extracted teeth on the bitewing radiographs using an AI model based on the a multilayer perceptron neural network. In this study, while the 0.717 ROC area value was obtained by best one of the 25 examiners, AI model achieved as 0.884 for an ROC area value. Taking into consideration all examiners, the diagnostic improvement was found 39.4% using AI model [50]. Lee et al. [15] assessed the effect of a pretrained GoogLeNet Inception v3 CNN model for perception of tooth decay on dental periapical images. The accuracy rate of tooth decay detection models for premolar, molar, and premolar-molar teeth were found as 89.0%, 88.0%, and 82.0%, respectively. The deep-CNN model obtained an AUC of 0.917 on premolar, an AUC of 0.890 on molar, and an AUC of 0.845 at 95% CI level on both premolar and molar models. The premolar tooth decay detection model achieved the best AUC rate and this model showed remarkable success rather than other caries detection models [15]. Khan et al. [51] investigated automated feature segmentation of common radiographic findings including tooth decay, alveolar bone loss, and interradicular radiolucencies in dental periapical images with DL-based architectures including U-Net, XNet, Segnet, U-Net + Densenet. The performance of caries segmentation with U-Net + Densenet achieved the best result with an mIoU rate of 0.428 and Dice coefficient value of 0.532 in the validation dataset. In the test dataset, mIoU and Dice coefficient value for caries segmentation with U-Net + Densenet121 were found as 0.194 and 0.239, respectively [51]. Cantu et al. [16] applied a deep-learning model to segment tooth caries on dental bitewing radiographs and they hypothesized that deep learning-based AI model significantly can detect more accurate than individual dentists. In this study, U-Net model as a DL algorithm was used and it trained on 3293 annotated bitewing images. In this study, accuracy, sensitivity, specificity, and F1 score of the AI model were found as 0.80, 0.75, 0.83, and 0.73, respectively. Mean accuracy value of dentists was significantly lower at 0.71. The AI model had 0.75 of sensitivity rate and it was remarkable and essentially higher than

Table 2 Predictive performance measurement using the AI model (CranioCatch, Eskisehir, Turkey) in external test data and comparing to 5 different experienced observers

	True positive (TP)	False positive (FP)	False negative (FN)	Sensitivity	Precision	F1 score
Caries detection						
CranioCatch	235	65	69	0.77	0.78	0.78
Observer 1	276	17	28	0.91	0.94	0.92
Observer 2	181	2	123	0.60	0.99	0.74
Observer 3	279	40	25	0.92	0.87	0.90
Observer 4	271	45	33	0.89	0.86	0.87
Observer 5	138	4	166	0.45	0.97	0.62
Caries segmentation						
CranioCatch	231	35	73	0.76	0.87	0.81
Observer 1	260	19	44	0.86	0.93	0.89
Observer 2	181	2	123	0.60	0.99	0.74
Observer 3	271	33	33	0.89	0.89	0.89
Observer 4	281	40	23	0.92	0.88	0.90
Observer 5	139	4	165	0.46	0.97	0.62

Observer 1—10 years experienced dentomaxillofacial radiologist, **Observer 2**—2 years experienced assistant-dentomaxillofacial radiologist, **Observer 3**—10 years experienced dentomaxillofacial radiologist, **Observer 4**—10 years experienced restorative dentistry specialist, **Observer 5**—3 years experienced assistant-restorative dentistry specialist

Table 3 Comparison of performance for caries detection presented by previous studies in the literature

Name of author	Year	Image type	Dataset size	Network	Outcomes
Kositbowornchai et al. [14]	2006	CCD camera and intra-oral digital radiographs	23 CCD 23 digital radiographs (extracted teeth images)	Learning vector quantization (LVQ)	The sensitivity and specificity rate of tooth caries perception by the CCD camera and digital radiographs were found as 0.77, 0.85 and 0.81, 0.93, at 95% confidence internal (CI) level, respectively
Devito et al. [50]	2008	Bitewing	40 premolar and 40 molar teeth (extracted teeth images)	Multilayer perceptron neural network	0.717 ROC area value was obtained by best one of the 25 examiners. AI model achieved as 0.884 for an ROC area value
Lee et al. [15]	2018	Periapical	3000	GoogLeNet Inception v3 CNN	The accuracy rate of tooth decay detection models for premolar, molar, and premolar-molar teeth were found as 89.0%, 88.0%, and 82.0%, respectively. The deep-CNN model obtained an AUC of 0.917 on premolar, an AUC of 0.890 on molar, and an AUC of 0.845 at 95% CI level on both premolar and molar models
Casalegno et al. [17]	2019	NILT	217	U-Net and an encoding path inspired by the structure of the VGG-16 classifier	Their model obtained 83.6% and 85.6% of area under the ROC rate for occlusal and interproximal tooth caries, respectively, for the classification of the presence or absence of tooth caries
Schwendicke et al. [19]	2020	NILT	226 extracted posterior teeth (113 premolars and 113 molars)	Resnet18, Resnext50	The mean AUC was found as 0.74 at 95% CI value. Sensitivity and specificity were found as 0.59 and 0.76, respectively
Geetha et al. [49]	2020	Periapical	105	Back-propagation neural network (BPNN)	Accuracy, receiver operating characteristic curve (ROC) area, precision-recall curve (PRC) area values of the suggested diagnostic system were 97.1%, 0.977 and 0.987, respectively
Khan et al. [51]	2020	Periapical	206	U-Net, XNet, Segnet, U-Net + Densenet	The performance of caries segmentation with U-Net + Densenet achieved the best result with an mIoU rate of 0.428 and Dice coefficient value of 0.532 in the validation dataset. In the test dataset, mIoU and Dice coefficient value for caries segmentation with U-Net + Densenet121 was found as 0.194 and 0.239, respectively
Cantu et al. [16]	2020	Bitewing	3293	U-Net	accuracy, sensitivity, specificity and F1 score of the AI model were found as 0.80, 0.75, 0.83, 0.73, respectively

Table 3 (continued)

Name of author	Year	Image type	Dataset size	Network	Outcomes
Present study	2021	Bitewing	613	VGG-16 U-Net	Sensitivity, precision and F1 score was found as 0.84, 0.84, 0.84 for detection model and 0.81, 0.86, 0.84 for segmentation model, respectively, in internal dataset. Sensitivity, precision and F1 score was found as 0.77, 0.78, 0.78 for detection model, 0.76, 0.87, 0.81 for segmentation model, respectively, in external dataset

sensitivity rate of dentists (0.36). Specificity rate of the AI model (0.83) was not remarkable lower than these dentists (0.91). Most of the dentists except one had low sensitivity rate for early enamel caries lesions [16]. In the presented study, both detection and segmentation model for tooth caries were developed. While VGG-16 was used for the detection of caries, U-Net was used for the segmentation of caries to the development of AI model. Data augmentation methods were applied training dataset to the development of both models. Sensitivity, precision, and F1 score were found as 0.84, 0.84, and 0.84 for detection model and 0.81, 0.86, and 0.84 for segmentation model, respectively in internal dataset. In external dataset, AI models were compared to 5 different observers having different experiences. Sensitivity, precision and F1 score were found as 0.77, 0.78, and 0.78 for detection model, 0.76, 0.87, and 0.81 for segmentation model in external dataset, respectively. When evaluating their F1 scores, AI models showed higher performance than 2 years experienced assistant-dentomaxillofacial radiologist and 3 years experienced assistant-restorative dentistry specialist, AI models had lower success than experienced experts in external dataset. Comparing to other studies; only presented study proposed both detection and segmentation models, differently using bitewing radiographs in the literature (Table 3). Beside, only a study conducted by Cantu et al. [16] using bitewing radiographs using U-Net model is available to caries segmentation in the literature. Presented study results have better value comparing to this study in terms of sensitivity, specificity, and F1 score. The limitation of our study is that the model is obtained by training with radiographs taken at the same parameters and obtained in a single center. In addition, our sample size is lower than the other study. These limitations should be eliminated in future studies.

In conclusion, CNN-based AI algorithms can have the potential to detect and segmentation of dental caries accurately and effectively in bitewing radiographs. Deep learning-based AI algorithms have the potential to help clinicians in routine clinical practice for fast and trustworthy detecting the tooth caries. The physician can be assisted in the detection of caries that may be overlooked due to factors including tiredness, experience differences, carelessness, etc. The use of these algorithms in clinical practice can provide to important benefit to physicians as a clinical decision support system in dentistry.

Appendix A

Eskisehir Osmangazi University Faculty of Dentistry Dental-Artificial Intelligence (AI) Laboratory has advanced technology computer equipment's including **Dell PowerEdge T640 Calculation Server** (Intel Xeon Gold 5218 2.3G, 16C/32 T, 10.4GT/s, 22 M Cache, Turbo, HT (125 W)

DDR4-2666, 32 GB RDIMM, 3200MT/s, Dual Rank, PERC H330 + RAID Controller, 480 GB SSD SATA Read Intensive 6Gbps 512 2.5in Hot-plug AG Drive), **PowerEdge T640 GPU Calculation Server** (Intel Xeon Gold 5218 2.3G, 16C/32 T, 10.4GT/s, 22 M Cache, Turbo, HT (125 W) DDR4-2666 2, 32 GB RDIMM, 3200MT/s, Dual Rank, PERC H330 + RAID Controller, 480 GB SSD SATA Read Intensive 6Gbps 512 2.5in Hot-plug AG Drive, NVIDIA Tesla V100 16G Passive GPU), **PowerEdge R540 Storage Server** (Intel Xeon Silver 4208 2.1G, 8C/16 T, 9.6GT/s, 11 M Cache, Turbo, HT (85 W) DDR4-2400, 16 GB RDIMM, 3200MT/s, Dual Rank, PERC H730P + RAID Controller, 2 Gb NV Cache, Adapter, Low Profile, 8 TB 7.2 K RPM SATA 6Gbps 512e 3.5in Hot-plug Hard Drive, 240 GB SSD SATA Mixed Use 6Gbps 512e 2.5in Hot plug, 3.5in HYB CARR S4610 Drive), **Precision 3640 Tower CTO BASE workstation** (Intel(R) Xeon(R) W-1250P (6 Core, 12 M cache, base 4.1 GHz, up to 4.8 GHz) DDR4-2666, 64 GB DDR4 (4 X16GB) 2666 MHz UDIMM ECC Memory, 256 GB SSD SATA, Nvidia Quadro P620, 2 GB), **Dell EMC Network Switch** (N1148T-ON, L2, 48 ports RJ45 1GbE, 4 ports SFP + 10GbE, Stacking).

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Declarations

Ethical approval All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2008.

Informed consent Informed consent was obtained from all patients for being included in the study.

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