



Detecting the presence of taurodont teeth on panoramic radiographs using a deep learning-based convolutional neural network algorithm

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Received: 4 February 2022 / Accepted: 30 April 2022 / Published online: 25 May 2022
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Abstract

Objectives Artificial intelligence (AI) techniques like convolutional neural network (CNN) are a promising breakthrough that can help clinicians analyze medical imaging, diagnose taurodontism, and make therapeutic decisions. The purpose of the study is to develop and evaluate the function of CNN-based AI model to diagnose teeth with taurodontism in panoramic radiography.

Methods 434 anonymized, mixed-sized panoramic radiography images over the age of 13 years were used to develop automatic taurodont tooth segmentation models using a Pytorch implemented U-Net model. Datasets were split into train, validation, and test groups of both normal and masked images. The data augmentation method was applied to images of trainings and validation groups with vertical flip images, horizontal flip images, and both flip images. The Confusion Matrix was used to determine the model performance.

Results Among the 43 test group images with 126 labels, there were 109 true positives, 29 false positives, and 17 false negatives. The sensitivity, precision, and *F1*-score values of taurodont tooth segmentation were 0.8650, 0.7898, and 0.8257, respectively.

Conclusions CNN's ability to identify taurodontism produced almost identical results to the labeled training data, and the CNN system achieved close to the expert level results in its ability to detect the taurodontism of teeth.

Keywords Taurodontism · Artificial intelligence · Deep learning · Panoramic radiographs · Dentistry

Introduction

Taurodontism is a condition in which the pulp chamber of a tooth is substantially expanded and furcation displaces to the apical area. This developmental condition can be present in both healthy people and people with syndromes, including Down syndrome, ectodermal dysplasia, and Klinefelter syndrome, among others. Taurodontism can also be seen with anomalies such as Amelogenesis imperfecta, cleft palate, microdontia, and dens invaginatus [1, 2]. Taurodontism is thought to be caused by invagination failure in the Hertwig epithelial root sheath; however, its etiological causes are unknown [3].

Taurodontism can cause some difficulties during endodontic, orthodontic, and/or prosthetic procedures, and has

been reported to increase pulp exposure during dental procedures [4]. It may cause difficulties in pulpectomy, canal preparation, and filling in endodontics, as the shifting of furcation to the apical triad may complicate the extraction of the effected tooth [5]. Taurodontism can appear unilaterally or bilaterally, and it might affect a single tooth or several teeth. Taurodontism most frequently affects molar teeth [1, 5–7] and may require diverse treatment approaches [6]. Teeth appear clinically normal in taurodontism [8], but it is usually detected by conventional radiographs (panoramic, intraoral, etc.) or cone-beam computed tomography (CBCT) [9].

The term “artificial intelligence” (AI) originated in the 1950s and refers to the concept of building machines capable of performing tasks that are typically performed by humans [10]. The field of Artificial Intelligence (AI) is concerned with teaching machines how to learn, problem-solve, and analyze in ways similar to human beings. Machine learning is a process for achieving AI by building algorithms to

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teach machine behavior through examples and emulation. Deep learning (DL) is an AI method used to program automated decision-making for various clinical tasks. DL techniques, created through the development of artificial neural networks, enable the automatic categorization of datasets and enables learning from data via multi-layer convolutional neural networks (CNN). By functioning like interconnected neurons in the human brain, CNN can learn adaptive image features and perform image classification [11].

AI techniques like CNN are a promising breakthrough because they can help clinicians analyze medical imaging, diagnose diseases, and make therapeutic decisions. AI studies using CNNs [12–26] have also made progress in the field of dentistry. The present study aims to develop and evaluate the function of CNN designed to diagnose teeth with taurodontism in panoramic radiography.

Materials and methods

Study design

In this study, automatic taurodont tooth segmentation models (CranioCatch, Eskisehir, Turkey) were produced in panoramic radiographs using a Pytorch implemented U-Net model. Eskisehir Osmangazi University Non-interventional Clinical Research Ethics Board (decision date, meeting number and decision number: 06.08.2019/14) authorized the study protocol. The principles of the Helsinki Declaration were followed in the study.

Data sources

Included in the study were 434 anonymous panoramic radiographs of patients over the age of 13 years obtained from January 2018 to January 2020 from the radiology archive of the Department of Oral and Maxillofacial Radiology of Inonu University Faculty of Dentistry. Gender differences were not considered. Radiographs were achieved using the Planmeca Promax 2D Panoramic System (Planmeca, Helsinki, Finland) using the 68 kVp, 14 mA, and 12 s. image acquisition parameters.

Labeled training data

A dentomaxillofacial radiologist, a pediatric dentist, and an endodontist, all three with at least 5 years of experience, identified the labeled training data for the panoramic radiographs using CranioCatch Annotation Tool (Eskisehir, Turkey). A tooth with an apically displaced pulp chamber which did not show the usual constriction of the pulp at the cemento-enamel junction and had an apically displaced furcation area was considered as a taurodont [27] (Fig. 1). The



Fig. 1 Normal (cynodontic) and taurodontism on a panoramic radiograph slice of the lower left second mandibular teeth. **a** A cynodontic (taurodont index; 12) lower left second mandibular tooth in a 17-year-old female patient. **b** The presence of taurodontism (taurodont index; 43) in the lower left second mandibular tooth in another female patient of the same age

Table 1 Taurodontism index values in the determination of taurodontism in teeth

	TI
Normal (cynodont)	< 20
Hypotaurodont	20–30
Mesotaurodont	30–40
Hypertaurodont	> 40

TI taurodontism index

index value for each tooth identified in the taurodont. The ratio of the height of the pulp chamber to the length from the roof of the pulp chamber to the root apex multiplied by one hundred was recorded [28]. Molar teeth with a taurodontism index (TI) above 20 were included in the study (Table 1, Fig. 2). Experts were asked to draw polygonal boxes around all the taurodont teeth included in the study on panoramic radiographs independently. Standard monitor settings and lighting conditions were used for images. If the experienced dentists did not agree on a diagnosis, even after discussion, the diagnosis was considered inconsistent and the image was excluded.

Segmentation model

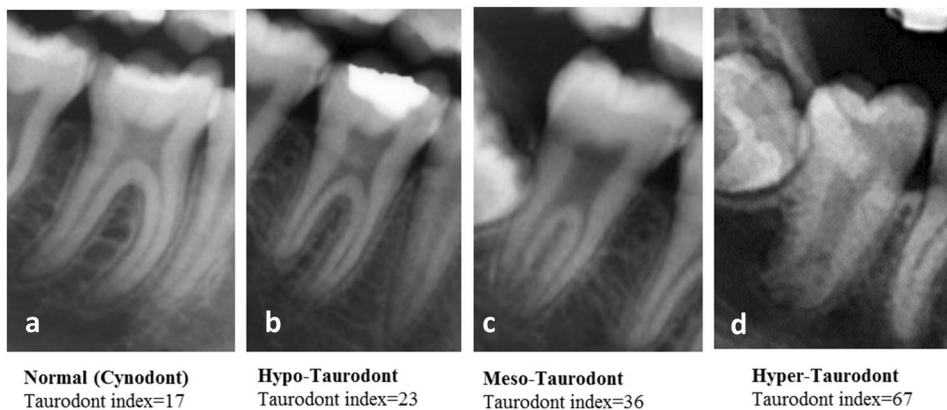
434 anonymized, mixed-sized panoramic radiography images were resized to 1024 × 512 diameter and cropped so that lower and upper jaw teeth appeared in the frame. Surrounding hazy images were cleared by applying contrast limited adaptive histogram equalization (CLAHE). Masked images were generated from labels, and datasets were split into train, validation, and test groups of both normal and masked images.

Training group 348 (1080 labels).

Training-mask group 348 (1080 labels).

Validation group 43 (126 labels).

Fig. 2 The variation in tooth root shape from normal to severe taurodontism is shown in panoramic sections



Validation-mask group 43 (126 labels).

Test group 43 (126 labels).

Test-mask group 43 (126 labels).

The data augmentation method was applied to images of trainings and validation groups with vertical flip images, horizontal flip images, and both flip images. After the data augmentation, the images of groups were as follows:

Training group 348 (1080 labels) × 4 = 1392 (4320 labels).

Training-mask group 348 (1080 labels) × 4 = 1392 (4320 labels).

Validation group 43 (126 labels) × 4 = 172 (504 labels).

Validation-mask group 43 (126 labels) = 172 (504 labels).

Test group 43 (126 labels).

Test-mask group 43 (126 labels).

Deep-convolutional neural network (CNN) architecture

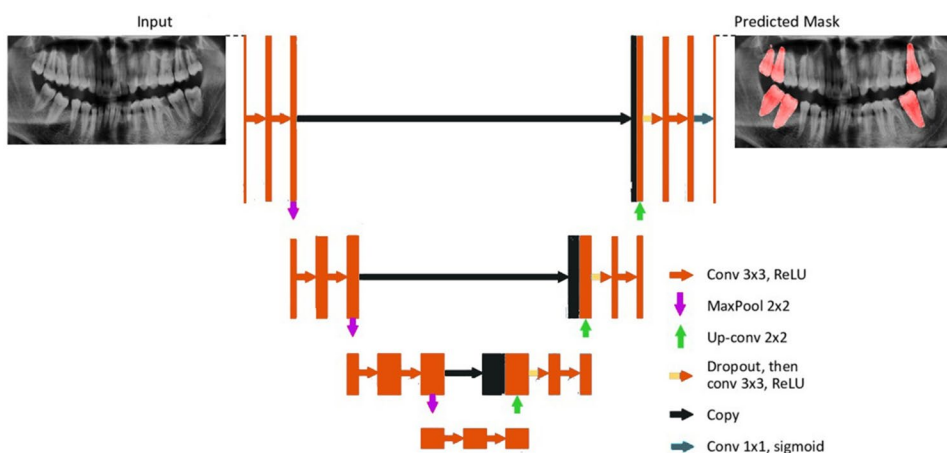
U-Net is a fully convolutional neural network whose main purpose is to segment medical images by estimating the class of each pixel in the image. As its name suggests, U-net architecture is “U” shaped and divided into three parts: the

encoding or down-sampling path, the bottleneck, and the decoding and up-sampling path. The coding path consists of many coding blocks. After each block, the map feature numbers multiply so that the model can efficiently learn complex structures. The bottleneck between the down-sampling and up-sampling paths consists of two convolutional layers. The essence of the U-net architecture lies in the decoding part. The U-Net model works incrementally by encoding the input and finding its deep features, which are then decoded using deconvolution and combined with features of the same dimensions into a channel [29] (Fig. 3).

Training

Python, an open-source programming language (version 3.6.1; Python Software Foundation, Wilmington, DE, USA), was used to develop the AI algorithm. The PyTorch library was used for creating the AI algorithm within the U-Net network. The training method was applied using computer equipment from Eskisehir Osmangazi Faculty of Dentistry Dental-AI Laboratory, including a Dell PowerEdge T640 Calculation Server (Dell Inc., Texas, USA), a Dell PowerEdge T640 GPU Calculation Server (Dell Inc., Texas,

Fig. 3 The system architecture of the U-Net algorithm



USA), and a Dell PowerEdge R540 Storage Server (Dell Inc., Texas, USA). The taurodont tooth segmentation model with Pytorch U-Net was trained with 600 epochs and the best model 548th epoch was saved. An AI model (CranioCatch, Eskisehir, Turkey) was used to automatically segment the taurodont teeth on panoramic radiographs (Fig. 4).

Assessment of model performance

The Confusion Matrix was used to determine the model performance. The metrics used to assess the performance of the taurodont tooth segmentation model were as follows:

True Positive (TP): The number of accurately segmented taurodont teeth.

False Positive (FP): The number of segmented teeth with no taurodontism.

False Negative (FN): The number of teeth with taurodont not segmented.

The performance metrics of the model were determined according to the formulas as follows:

Fig. 4 Diagram of the automatic taurodont tooth segmentation models on panoramic radiographs

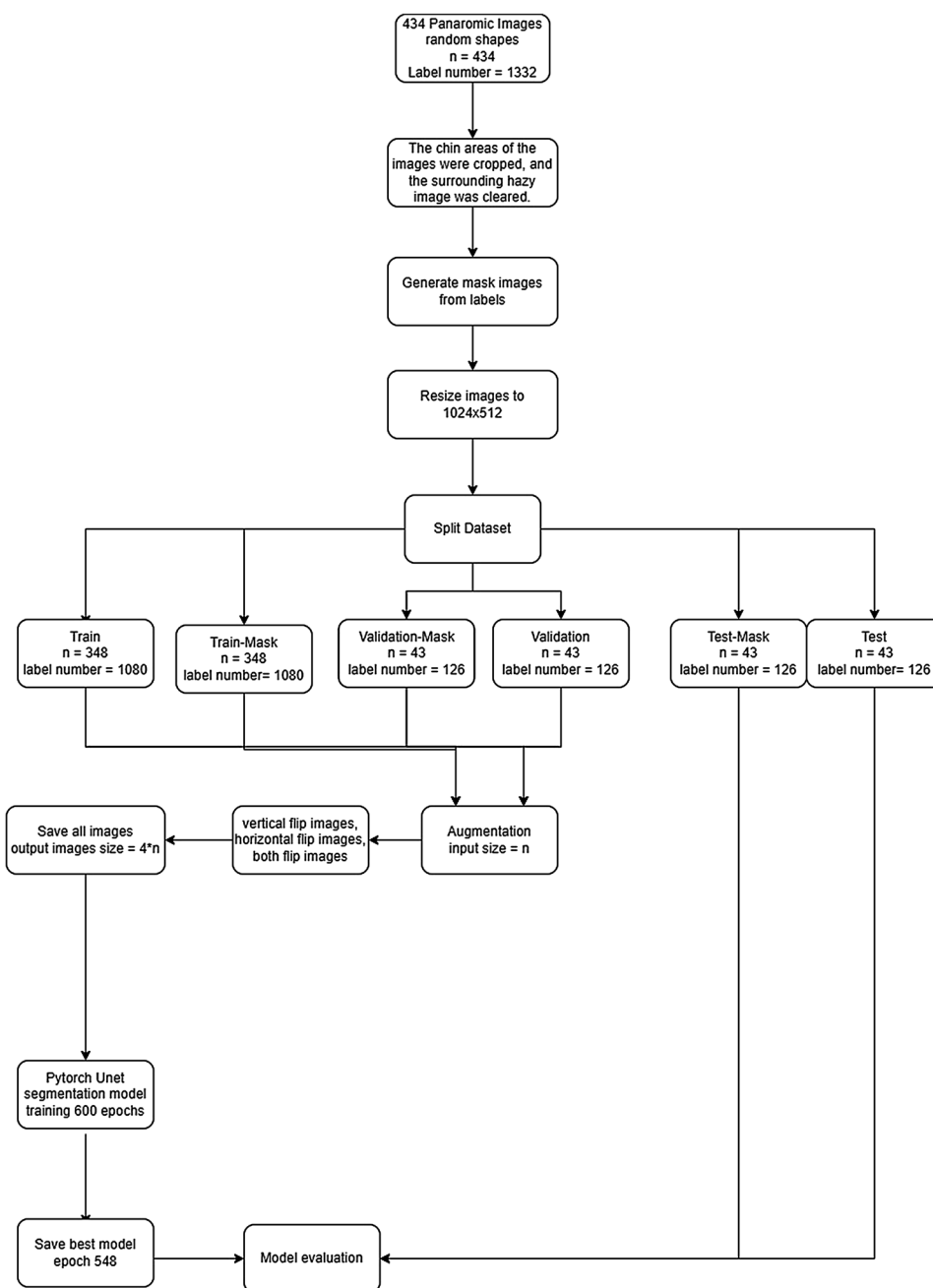


Table 2 Teeth separation in the test group based on taurodontism index scores

	Hypotaurodont <i>n</i> (%)	Mesotaurodont <i>n</i> (%)	Hypertaurodont <i>n</i> (%)
Maxilla (<i>n</i> = 63)	7 (11.1)	16 (25.4)	40 (63.5)
Mandible (<i>n</i> = 63)	32 (50.8)	14 (22.2)	17 (27)
Total (<i>N</i> = 126)	39 (31)	30 (23.8)	57 (45.2)

Table 3 Taurodontism index score averages of the teeth in the test group according to taurodontism types

TI	Minimum	Maximum	Mean (SD)
Hypotaurodont	20.31	29.70	26.30 (2.33)
Mesotaurodont	30	39.66	34.61 (3.25)
Hypertaurodont	40.51	100	82.55 (24.34)

TI taurodontism index, SD standard deviation

Table 4 Number of detected, undetected teeth and false detected in the test group using the AI model

Metric	Number
True positive (TP)	109
False negative (FN)	17
False positive (FP)	29

Sensitivity (Recall, True positive rate (TPR)): $TP / (TP + FN)$
 Precision (Positive predictive value (PPV)): $TP / (TP + FP)$
F1 Score: $2TP / (2TP + FP + FN)$

Results

A total of 126 labeled teeth with taurodontism (hypotaurodont; *n* = 39, mesotaurodont; *n* = 30, hypertaurodont; *n* = 57) in 43 panoramic radiographs were determined as the test group (Table 2). The mean TI scores of hypotaurodont, mesotaurodont, and hypertaurodont teeth in the test group were found to be 26.30 ± 2.33 , 34.61 ± 3.25 , and 82.55 ± 24.34 , respectively (Table 3).

Among the 43 test group images with 126 labels, there were 109 TPs, 29 FPs, and 17 FNs (Table 4). The sensitivity, precision, and *F1*-score values of taurodont tooth segmentation were 0.8650, 0.7898, and 0.8257, respectively (Table 5 and Fig. 5).

Discussion

CNN systems have recently gained popularity in the medical field, particularly for the analysis of radiological images [30]. Many studies [13–21] have shown CNN to

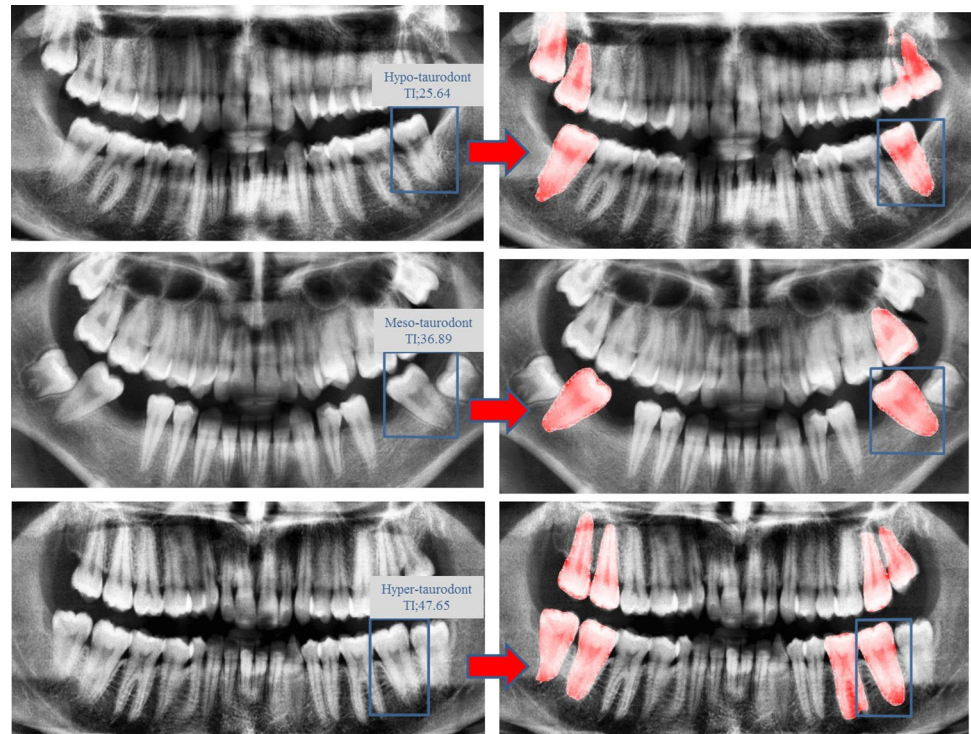
Table 5 Predictive performance measurement using the AI model

Measure	Value	Derivation
Sensitivity	0.8650	$TPR = TP / (TP + FN)$
Precision	0.7898	$PPV = TP / (TP + FP)$
<i>F1</i> -score	0.8257	$F1 = 2TP / (2TP + FP + FN)$

be successful at scanning radiographic images (periapical, bitewing, panoramic, CBCT, etc.) used in dentistry. Research conducted with conventional radiographic techniques [13, 15, 17, 18] using CNN to detect and number teeth described CNN as a promising technology for the future. Moderate and high success was achieved in studies evaluating panoramic radiographs of alveolar bone loss [12], teeth with periodontal problems [16], dental caries [21], apical lesions [22], vertical root fracture [23], root morphology [24, 25] and impacted teeth [26]. However, there was no study using CNN to evaluate teeth with taurodontism, so our study is a first in this respect. In this study, the CNN’s ability to identify taurodontism produced almost identical results to the labeled training data, and the CNN system achieved close to the expert level results in its ability to detect the taurodontism of teeth.

Artificial intelligence research in pediatric dentistry is a newly emerging field. In the study of You et al., clinically acceptable performance was obtained using the CNN model compared to a pediatric dentist experienced in detecting dental plaque in primary teeth [31]. Kılıç et al. concluded that fast regional-CNN for detecting and numbering the primary teeth of children in panoramic radiography images was a promising tool for automated charting of panoramic radiographs from children [13]. Caliskan et al. reported that a moderately deep CNN trained on a limited amount of image data showed satisfactory discriminatory ability to detect submerged molars on panoramic radiographs [26]. Mine et al. reported that CNN-based deep learning method is a promising approach to detect the presence of supernumerary teeth in early mixed dentition [32]. These studies can lead to the development and dissemination of pediatric dentistry-specific artificial intelligence by enabling collaboration between pediatric dentists and data scientists with the necessary expertise to apply big data sources to artificial intelligence.

Fig. 5 Automatic taurodont tooth segmentation on panoramic radiographs using the artificial intelligence algorithm (CranioCatch, Eskisehir—Turkey)



This study used a CNN-based deep learning technique to diagnose taurodont teeth by analyzing panoramic images. Despite drawbacks, such as two-dimensional imaging, distortion, and superposition of anatomical structures, panoramic radiographs are used to diagnose dental anomalies since they allow the entire dentition to be seen on a single film. Moreover, particularly for pediatric dentists, radiographing is a tolerable procedure to the patients, time-efficient, and offers low radiation exposure in the diagnosis and treatment planning of anomalies, such as taurodontism, where more than one or symmetrical teeth may be affected [13]. However, difficulties may arise in interpreting panoramic images due to subjective evaluations and differences between observers [12, 13]. AI can be used as a decision-support system for physicians and help reduce diagnostic errors caused by fatigue, especially in institutions with high workloads, and may capture details that are overlooked by inexperienced physicians [12]. In the field of dentistry, AI can also provide objective data for image standardization, data archiving, as well as for early diagnosing and treatment planning [12].

Blumberg et al. [27] noted that taurodontism can be described metrically and that a precise mathematical tool can be invaluable in accomplishing this task. In this study, the ratio-based “taurodont index” (TI) value developed by Shifman and Chananel for radiological classification with objective measurements was used for the diagnosis of taurodontism. Since one of the index variables is a measurement that includes the apex of the longest root, the lower limit of

our study was determined as 13 age r to maintain the root/crown ratio of the teeth, complete the root length and ensure standardization.

Taurodontism affects a wide range of dental procedures. Teeth with taurodontism are limited due to attrition, especially in maturity, and the completion of root formation, which affects which teeth can be used, especially in younger patients who are more likely to be under the care of an orthodontist or pediatric dentist. In orthodontic and prosthetic considerations, taurodontism limits the root surface area available for anchoring, as the absence of a cervical narrowing would deprive the tooth of its supportive action against crown overload [33]. Furthermore, taurodontism complicates endodontic therapy since it can cause problems during instrumentation and obturation in root canal treatment. Endodontic treatment of a taurodont tooth becomes more complex as the furcation shifts towards the apical third [34]. A modified filling technique has been developed, which involves combining lateral compaction in the apical region with vertical compaction in the elongated pulp chamber [35]. Physicians must be aware of the complex canal system to manage it successfully. This study aimed to diagnose only teeth with taurodontism, because the CNN technique is based on incremental improvement phases, and the results of preliminary steps have employ for transfer learning. However, there are variations of teeth with taurodontism (hypotaurodont, mesotaurodont, and hypertaurodont) [3, 4], and several indices are used to classify them [4]. The taurodontic teeth indicated by the experts’ TI measurements were

labeled and introduced to the artificial intelligence system in this study. The second stage involves using a deep learning system to score TIs and categorizing them based on the results. Without taking any measurements, physicians can get information on the vertical length of the pulp chamber and the predicted locations of the canal entrances. Furthermore, employing AI to determine the type of taurodontism can aid in the assessment of root canal treatment risks.

The segmentation of multi-rooted teeth is more complicated than single-rooted teeth. The maxillary molars teeth are multi-rooted and multiple roots can overlap with the maxillary sinus, making it difficult to automate the segmentation of these teeth [14]. Given that studies show that molar teeth [1, 5–7] and the maxilla [1, 7, 36] are the most common areas affected by taurodontism, the difficulty in segmenting molar teeth may also occur in the diagnosis of taurodontism. Since this study was the first study in which taurodont teeth were diagnosed, it was not evaluated whether there was a difference in the detection of taurodont teeth in the maxilla and mandible with AI, and in future studies, subgroup analysis for the maxilla and mandible could be performed.

Conclusion

In this study, CNN models performed well in the detection of taurodont teeth on panoramic radiographs. Although further improvements are needed for clinical applications, the CNN-based deep learning approach is a promising approach for supporting dentists in dental practice and plays a precious role in saving time. In future studies CNN could be extended to evaluate different types of taurodontism or to diagnose using different types of X-ray images, such as periapical, CBCT.

Author contributions SD, ISB, and EFY conceived the ideas; GE, SD, and EFY collected the data; OC, EB, and ISB analyzed the data; SD, ISB, and GE: writing—original draft; ALFC, RJ, and KO: supervision.

Funding This work has been supported by Eskişehir University Scientific Research Projects Coordination Unit under Grant number 202045E06.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All the 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 (5). Informed consent was obtained from all the patients for being included in the study. This article does not

contain any studies with human or animal subjects performed by the any of the author.

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