Chapter 1

# Artifical Intelligence in Oral Radiology

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**Abstract**

Clinical dentistry relies heavily on dental imaging. X-ray, particularly panoramic imaging, is the most frequent imaging modality, though not the only one. Radiologic images are easily acquired. They enable dental practitioners to uncover numerous disorders that would otherwise go undetected because many oral diseases have no clinical indications or symptoms. Medical imaging technology has advanced significantly in recent years. One of the most current research areas is the development of automatic analysis methods for radiography images based on anatomical landmark recognition or picture segmentation. This technology discovery is particularly intriguing in dentistry since it has the potential to help professionals ease and speed up treatment planning. Since dental images are digitally recorded data that can be easily translated into computer language, they were the first link between Artificial Intelligence (AI) and dentistry. Deep Learning is the primary strategy to developing automatic analysis systems among the different AI approaches because to its nature of providing digitally coded pictures that can be more readily translated into computer language. As a result, radiology is seen as presenting a clearer way for AI into healthcare. In addition to being able to avoid reviewing and reporting on a huge number of dental images, dentists hope that using AI diagnostic models would enable them to work more efficiently and provide more accurate results when it comes to the final diagnosis of various diseases. The aim of this section is to review the current and potential uses of AI applications in oral radiology and to examine the innovations and possible contributions to the field.

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https://doi.org/10.58830/ozgur.pub431.c1874

## 1. Artificial Intelligence-An Overview

The term 'Artificial Intelligence' was first used by John McCarthy in 1956, and was later defined in 2004 as "the science and engineering of making intelligent machines, especially intelligent computer programs. Artificial Intelligence (AI) is the use of computers to understand human intelligence. It is not limited to techniques that are visible in biology (1). Even while academic, business, and government organizations are becoming more and more interested in artificial intelligence (AI), there is still no consensus on what AI is and what it involves. The field has greatly developed since its early definition. In the current era of rapid technological advancement and exponential growth in large data sets, commonly referred to as 'big data', Artificial Intelligence (AI) has transitioned from a theoretical concept to a tangible application on an unprecedented scale (2-4). AI has gained notable momentum and, if harnessed appropriately, has the potential to exceed expectations across various application sectors. AI has become integrated into many facets of society, including autonomous driving cars, real-time data analysis, online streaming, purchase recommendations, advertisements, and fraud detection.

It is a complex field with no unified criteria for its definition or classification of its sub-fields. This is mainly because domains and subdomains are related subsets of AI, and most applications developed interconnect them. The environment embraces intertwined applications and theoretical advancements, with fuzzy boundaries (2,4,5). Nowadays, medicine most commonly uses a branch of AI called machine learning (ML) and, more recently, deep learning (DL) (6-10) (Figure 1).

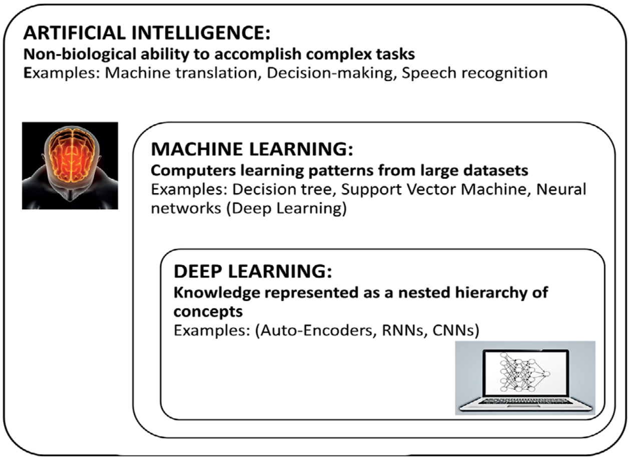


*Figure 1. Diagram demonstrating how DL is a subset of ML, which is a subset of AI. Each portion of this graphic offers an overview of the concept as well as a few examples of AI technology (2).*

### 1.1. Machine Learning, Deep Learning and Artificial Neural Networks

A computer program is given a series of tasks to accomplish in machine learning, and it is claimed that the machine has learnt from its experience if its measured performance in these tasks improves over time as it gains more and more practice performing them. This suggests the system is generating decisions and projections based on past data. Consider computer software that learns to identify cancer based on medical information from patients. When it analyzes medical research data from a wider population of patients, its performance will improve due to knowledge accumulation (5, 11).

Machine learning is the capacity to autonomously adapt with little to no human involvement in artificial intelligence (AI), and deep learning is a form of machine learning that employs neural networks to imitate the human brain's learning mechanism. There is a significant gap between these two concepts. Deep learning can adapt to new conditions and compensate for its own flaws, despite the fact that it requires more data to train on (2,4-6). Machine learning, on the contrary hand, allows for training on smaller datasets but requires more human interaction to learn and rectify its faults. Human interaction is required for machine learning to categorize data and highlight qualities. A deep learning system, on the other hand, seeks to acquire these characteristics without any human intervention. In the most basic terms, machine learning works like an obedient robot. Data patterns are examined in order to develop predictions. Deep learning is similar to imagining a robot that learns on its own. It can learn more complex patterns and make autonomous predictions.

Artificial neural networks are an area of machine learning. It is a network model comprised of neurons with numerous parameters and layers between input and output. DL is based on neural network topologies (Figure 2). As a result, they are known as deep neural networks (2,4,5,8). DL enables independent learning of traits and their hierarchical representation at numerous levels. In contrast to traditional machine learning methodologies, this robustness is the outcome of deep learning's strong process; in short, deep learning's whole architecture is employed for feature extraction and modification. The early layers do rudimentary data processing or learn simple features, and the result is passed to the later layers, which are in charge of learning intricate features (2,4-6).

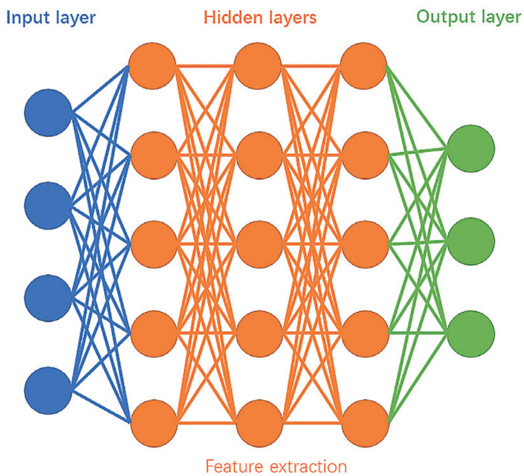


*Figure 2. Schematic diagram of deep learning*

## 2. AI in Oral Radiology

Artificial intelligence basically aims to solve possible problems that can be solved with human mind and skill with machines. In dentistry, artificial intelligence applications in areas ranging from caries diagnosis, detection of pathologies, planning orthodontic treatment of crowded teeth, dental implant construction with robotic surgery, as well as organising patient appointments, carrying out insurance and paperwork, and keeping medical anamnesis records attract attention (13-19). In radiology, it is seen that artificial intelligence provides easier access to medicine due to its ability to produce digitally encoded images that can be more easily translated into computer language. All data about the patient, including patient history, demographic information, lifestyle and genetic factors, can be recorded. Thanks to these large data sets, classifier and predictive artificial intelligence models can be created. These models will help to prioritise risk factors and predict the long-term consequences of diseases by exploring the relationships between diseases and patient data (20).

Deep learning algorithms are currently being used to interpret medical images, and they have shown promise in a variety of applications. Dental radiology research has received attention due to the use of image processing technologies (6,7,21-24). It is feasible to recognize the structures to be investigated in a radiograph, as well as separate (segment) or categorize the remaining data in the image, using artificial learning models (25-28). Artificial intelligence applications in oral radiology include automated dental radiograph interpretation, radiographic landmark detection, diagnosis of vertical root fractures, estimation of dental age, direct evaluation of bone architecture using orthopantomographs (OPGs), 3D visualization for orthodontic applications, determination of bone mineral density (BMD) using OPGs to predict osteoporosis ( 29-31).

## 2.1. Radiographic Landmark and Object Detection

AI distinguishes osseous and sof ttissue features by employing Convolutional Neural Network (CNN) (31,32). CNN immediately locates landmarks in places that are partially concealed, have discrepancies, or are lapping and are not visible to the human eye. By expanding on each pixel in the picture, the AI-based neural network algorithms correctly recognize the new anatomical features. Neural networks on panoramic radiography can recognize and count the teeth in one or more notation systems (33).

Uğurlu (34) used an artificial intelligence model that can detect cephalometric landmarks automatically, allowing for the automatic analysis of cephalometric radiographs, which play an important role in dental practice and are used routinely in the diagnosis and treatment of dental and skeletal disorders. There were 1620 lateral cephalograms taken, with 21 landmarks included. The coordinates of all landmarks in the 1620 images were acquired to create a labeled data set: 1360 were utilized as a training set, 140 as a validation set, and 180 as a testing set. A convolutional neural network-based artificial intelligence technique for automated cephalometric landmark identification was created (Figure 3A-C). The presented artificial intelligence system (CranioCatch, Eskişehir, Turkey) was able to recognize 21 anatomic features in a lateral cephalometric radiograph. The sella point had the greatest success detection rate scores of 2 mm, 2.5 mm, 3 mm, and 4 mm, respectively, as 98.3, 99.4, 99.4, and 99.4. Although the success of automatic landmark detection with the developed artificial intelligence model was insufficient for clinical use, artificial intelligence-based cephalometric analysis systems appear offering for cephalometric analysis, which provides a basis for diagnosis, treatment planning, and follow-up in clinical orthodontics practice.

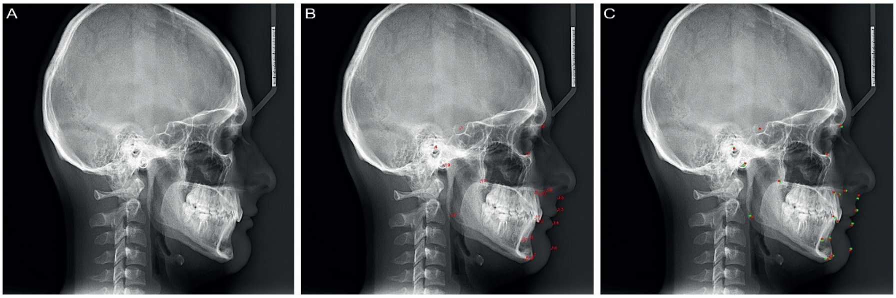


***Figure 3 A-C. Automatic detection of cephalometric points by the AI model. (A) Originalimage (B) Automatic landmark detection by AI model. (C) The comparison of landmark detection by expert and AI. Red: landmark location detected by expert. Green: landmark location detected by AI (34).***

Moreover, Yu et al. (35) showed modified DenseNet pre-trained with ImageNet weights using lateral cephalograms. The model's accuracy was 95.70% greater than that of five orthodontists. Park et al. (36) used YOLOv3 to recognize landmarks in 1311 cephalograms. The model was effective in detecting 80 landmarks with a 5% higher accuracy than top benchmarks.

A DL algorithm for automatically detecting teeth in panoramic radiography is considered a breakthrough in dental practice (37-39). In in order to test the usability of artificial intelligence technologies in dentistry, which are becoming widespread and expanding day by day, and to investigate ways to benefit more from artificial intelligence technologies; a tooth detection and numbering study was performed by Mertoğlu et al. (40) on panoramic radiographs using a deep learning software (Figure 4A-C). A radiographic dataset containing 200 anonymous panoramic radiographs collected from individuals over the age of 18 was assessed in this retrospective investigation. The images were separated into three groups: training (80%), validation (10%), and test (10%), and tooth numbering was performed with the DCNN artificial intelligence model. The D-CNN system has been successful in detecting and numbering teeth. of teeth. The predicted precision, sensitivity, and F1 score were 0.996 (98.0%), 0.980 (98.0%), and 0.988 (98.8%), respectively. The precision, sensitivity and F1 scores obtained in the study were found to be high, as 0.996 (98.0%), 0.980 (98.0%) and 0.988 (98.8%), respectively. Although the current algorithm based on Faster R-CNN shows promising results, future studies should be done by increasing the number of data for better tooth detection and numbering results.

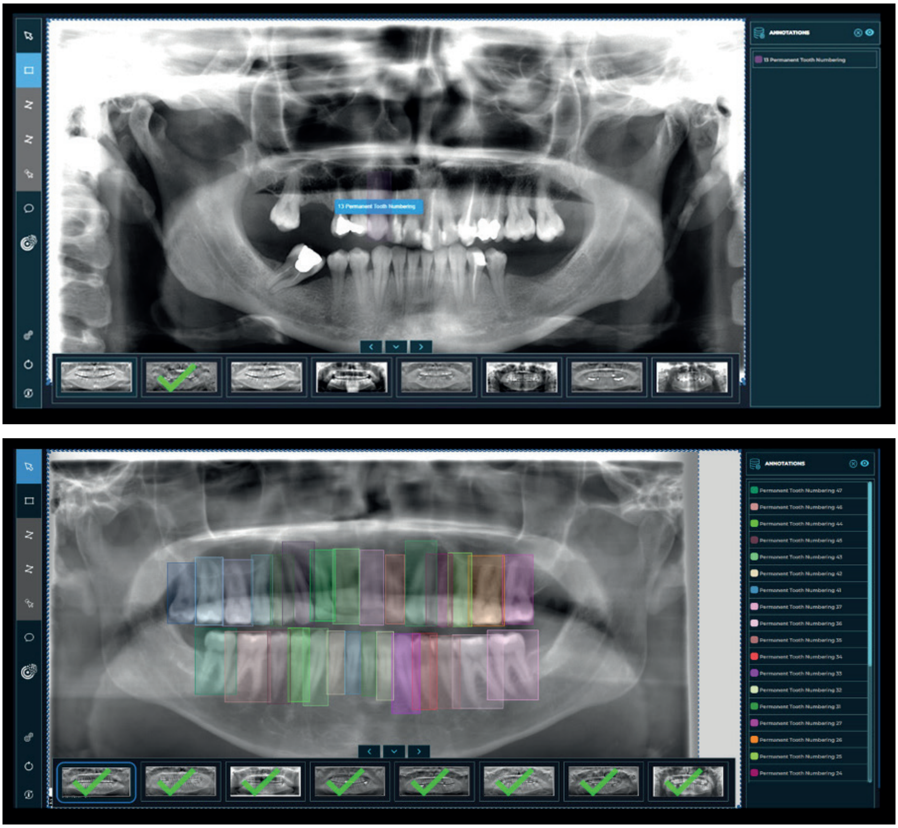

***Figure 4 A) Example of "Area detection" data labeling for tooth detection and numbering in panoramic radiography B) Automatic tooth detection and numbering model of CranioCatch (CranioCatch, Eskişehir, Türkiye) artificial intelligence software (40).***

Futhermore, Bilgir et al. assessed the diagnostic performance of an AI system based on a deep convolutional neural network approach for detecting and identifying teeth on panoramic radiographs.The trained model displayed a high sensitivity equivalent to that of an expert, with an average sensitivity of 0.987 and a precision of 0.9945 (41).

AI-based computer-aided detection and diagnosis are being used to further enhance the quality, efficiency, and price of ultrasound (US) imaging, resulting in a rise in US recognition for musculoskeletal examinations (42). Keser et al. (24) intended to assess the efficacy of a deep convolutional neural network (D-CNN)-based AI system for masseter muscle recognition and segmentation on US images. The U-net artificial intelligence deep learning model detected and segmented all test images, and when the success rate in image estimation was analyzed, the model's F1, sensitivity, and precision values were 1.0, 1.0, and 1.0, respectively. Consequently, softwares for dental imaging that is AI-based can help interpret images more rapidly and effectively.

### 2.2.Detection of Pathologies

Infection spread along the apex is common in everyday clinical practice, resulting in periapical granulomas, abscesses, and cysts. All of these lesions are detected using twodimensional (2D) imaging; however, some may be overlooked owing to poor contrast, incorrect procedures, or superimpositions (13). Identifying the dental locations prone to caries can help to decrease the incidence of these inflammatory outcomes. AI can precisely characterize the extent of lesions and assist in their identification via automatic segmentation (43,44). In addition, Orhan et al.'s results (22) show that the AI system had a 92.8% detection accuracy rate and could correctly identify 142 out of 153 periapical lesions on Cone Beam Computed Tomography (CBCT) scans. Artificial neural networks also have been used to identify cystic lesions (45).

In another study, a CNN was developed for the diagnosis of osteoporosis in panoramic radiographs, the radiographs detected by the algorithm were compared with expert physicians and it was stated that it distinguished osteoporosis with excellent accuracy (46). There is also a study that obtained results close to physicians with another CNN algorithm created to detect periodontitis by evaluating bone destruction levels in panoramic radiographs (47). 2D intraoral radiographs have also been used to detect periodontitis (48).

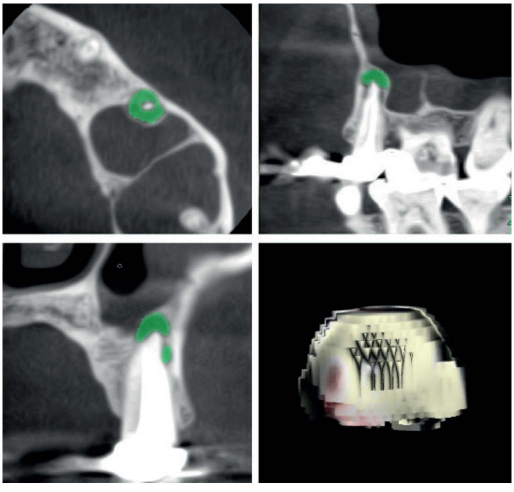

***Figure 5. Volume measurement using the manual segmentation method in detection of periapical lesions(22).***

In another research area, Kise et al. (49) evaluated the outcomes of deep learning and three novice radiologists on 100 patients with Sjogren Syndrome and 100 patients who had never been diagnosed. Deep learning showed 89.5, 90.0, and 89.0% accuracy in parotid gland outcomes based on ultrasound images taken from salivary glands, whereas radiologists had 76.7, 67.0, and 86.3% accuracy.

After training the neural network (NN) model using the clinical symptoms and diagnoses of 161 patients, Baş et al. (50) assessed the NN's capacity for diagnostic determination on 58 patients. They used clinical diagnosis, which is regarded as the gold standard, to compare the sensitivity and specificity of ANN in identifying TMD subgroups. Unilateral disc displacement with reduction detection of ANN was shown to have a sensitivity and specificity of 80% and 95%, whereas its success rate without reduction was determined to be 69% and 91%. In contrast to those without bilateral reduction, which were 37% and 100%, disc displacement sensitivity and specificity with bilateral reduction were 100% and 89%. To sum up, it is anticipated that AI models would be able to autonomously detect diseases on 3-D images, pinpoint an individual's unique risk for a disease, and assist physicians in therapeutic applications by assessing the likelihood of various treatment options by feeding on larger and more complete data sets.

## 3. Conclusion

Significant advancements in dentistry have been made in recent decades thanks to artificial intelligence technology, which is predicated on mimicking the ways in which the human brain functions. Dentists assume that by employing AI diagnostic models, they will be able to not only avoid reviewing and reporting on a huge number of dental images, but also boost their job efficiency and acquire more precise findings when it comes to the final diagnosis of various diseases.

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