Chapter 4

Artificial Intelligence Applications In Dentistry

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Abstract

In terms of new technologies that continue to have an impact on daily life, artificial intelligence (AI) covers a wide range. Due to the development of AI, it is now feasible to analyze large amounts of data, which enhances decision-making by supplying accurate information. Dentistry, which is intertwined with technology, is an area open to development with artificial intelligence applications. AI applications come to the fore in areas such as diagnosis of various pathologies, planning of complex treatments and robotic surgery. The aim of this section is to review the current and potential uses of AI applications in dentistry, to examine the innovations and possible contributions to the field.

Introduction

In the 1950s, the concept of creating machines that can carry out tasks that are typically handled by people became known as artificial intelligence (AI) (1-7). John McCarthy first proposed the idea of artificial intelligence in 1956 (8). Artificial intelligence is a branch of science and engineering that deals with the comprehension of "intelligent behavior" by computer systems and the development of objects that display this behavior. In other words, AI is the ability of machines to learn and solve problems by imitating human cognitive processes (9-11).

The goal of the computer science field of AI is to comprehend and create intelligent beings, frequently manifested as computer programs. It is a series of actions intended to carry out a certain task. In the past, hand-written rules were applied by artificially intelligent systems to the particular problems they were designed to tackle (5,6,11-13) The system had to be manually fine-tuned by subject-matter specialists, who also needed to have engineering expertise particular to the work at hand. For instance, a system

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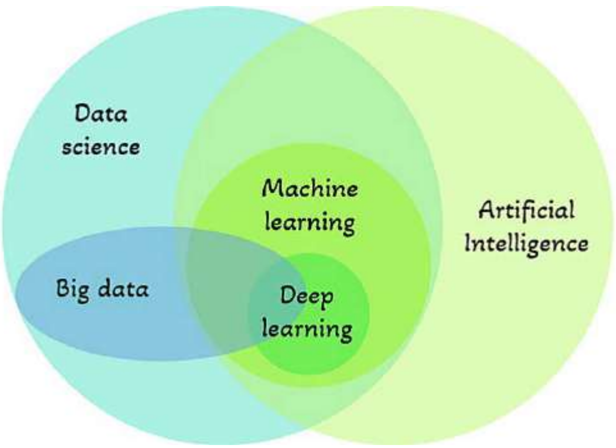
created to find lesions in medical imaging would search for lumps with an odd color and a certain form. The system's fine-tunable components may include a spectrum of colors that represent healthy tissue or the bare minimum lengths and widths of possible lumps. Nowadays, medicine most commonly uses a branch of AI called machine learning (ML) and, more recently, deep learning (12-16) (Figure 1).

Figure 1. Key elements of artificial ıntelligence systems. (17)



Machine learning

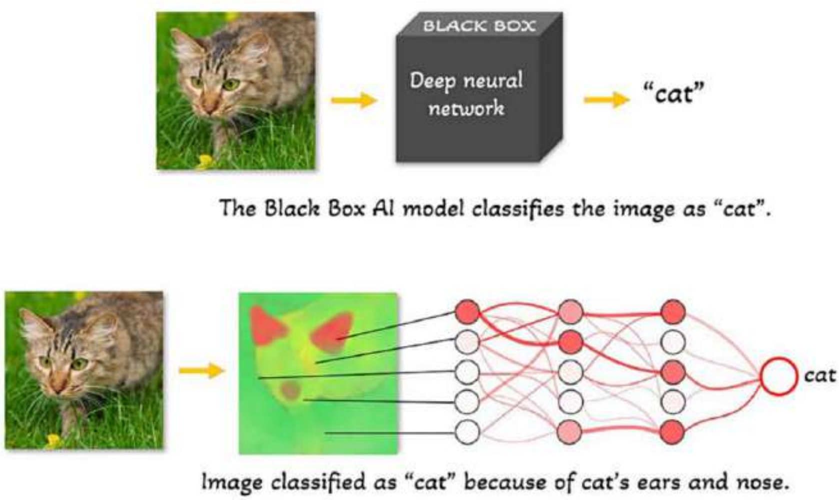
ML refers to the area of AI in which learning is carried out automatically without the need for data collection. ML is a subtype of AI that mimics the human brain by learning to solve problems, detecting patterns, correcting errors on its own, categorizing data, and carrying out these tasks repeatedly (1-3,12-14).

ML algorithms are trained to give an accurate specific answer by studying or learning from a large number of manually entered data. It is one of the parts in artificial intelligence that provides information to computer systems with data and observations without being programmed in the real sense. This allows the computer to correctly generalize a setting by adjusting parameters within the algorithm to achieve the fit between input and output data. For example, a machine learning algorithm can recognize or detect a lymph node as normal or abnormal in the head and neck image if trained by the radiologist by analyzing thousands of such images labeled as normal or abnormal (2,4,17,18). Feeding directly on medical data, ML can help prevent errors from cognitive bias or human bias.

Deep learning

It is part of representational learning that relies on multiple layers of learning to learn the representation of data with various distinctive features. Using the system in a hierarchical configuration, this algorithm creates multiple layers to detect simple features such as lines, edges, and textures to further and complex lesions or entire organs. Deep learning, from a comprehensive series of normal images, to a hierarchical standard of a particular image type can perform significantly better by learning its representation (1-5,18,20) (Figure 2).

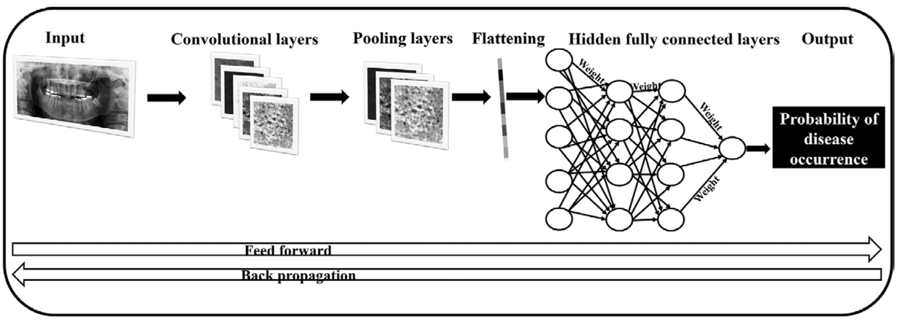
Figure 2. Schematic representation of working of Artificial Intelligence models. (a)Black box AI model. (b) Recent AI models (2)



Artificial neural networks

Artificial Neural networks (ANN) are computer systems inspired by the biological neural networks that make up the human brain. Such systems learn to perform tasks by considering examples, often without being programmed with task-specific rules (1-5,16,21). This includes a network of highly interconnected computer processors capable of learning from past examples, analyzing nonlinear data, processing imprecise information, and applying the model to independent data. The artificial neuron, a mathematical non-linear model that was modeled after the human neuron, is the fundamental component of any ANN (3,5,16). An artificial neural network is created that seeks to solve a particular problem, such image classification, by stacking and concatenating artificial neurons and linking those layers using mathematical operations. Neural networks are the most commonly used algorithms for image analysis today (19-23). There are several varieties of deep neural networks. Convolutional and recurrent neural networks (RNNs and CNNs) are both employed in practice. Speech and language are examples of the sequential input data that RNNs can handle. CNNs are trained to manage data having a topology resembling a grid, such as 2D and 3D images (21,24-26) (Figure 3).

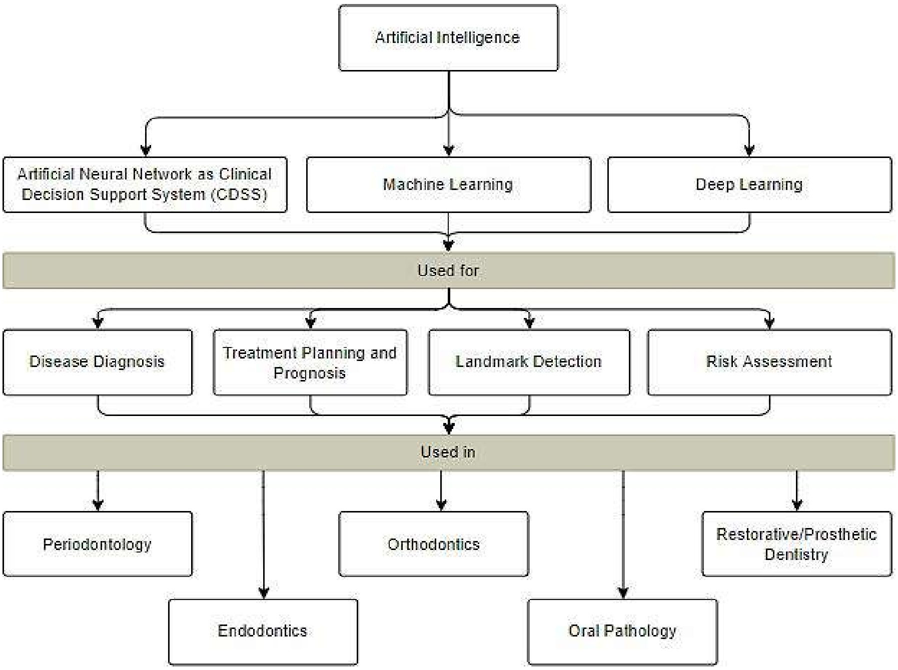
Figure 3. Example of a CNN used to predict dental diseases based on information extracted from a panoramic radiography (26)



Technology is developing quickly, often even exceeding scientific confirmations and breakthroughs. Modern tools may make it possible to combine inputs from several units, creating a more effective method for tackling challenging issues (26,27). This is unquestionably true in the field of oral healthcare, where the growth in information, data, and knowledge storage has prompted the creation of new technologies and ways for people to connect with machines. In this regard, the phrases AI, ML, and DL are now often used in a variety of areas of modern day life, including the medical field and dentistry (27-30).

Due to the demand for greater patient care and precise diagnosis, AI technology has impacted the healthcare industry. Studies on artificial intelligence (AI), which are developing and gaining traction, have the potential to transform and enhance numerous fields, including dentistry (4,5,16, 31-33) (Figure 4). These improvements are accelerated by factors including the rise in computing power, the ease of access to global knowledge, and the availability of big data that is suitable for AI applications in the healthcare sector. Studies on AI mostly try to use computers to solve potential issues that can be resolved using the human brain and talent. In this way, AI is comparable to a creature that is fed digital data (31-34). The accuracy, dependability, and effectiveness of machine learning models are influenced by the quality and quantity of digital data. Nowadays, technology is embedded into every aspect of dentistry. This indicates that it is an area that may be improved upon and employed for applications using artificial intelligence (2,3,5,15,16,31).

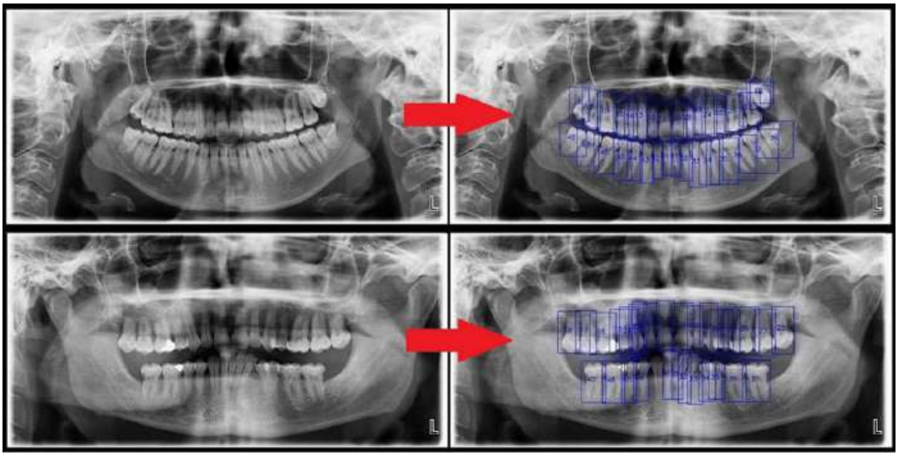
Figure 4. Applications of AI in different subfields of dentistry (35)



AI in In Dental Radiology

Deep learning algorithms have lately been used for medical image processing, and they have showed promise in a range of applications. Dental radiology research has been emphasized due to its adaptation of image processing tools (2,5,12,13,35,36). With artificial learning models, it is possible to detect the structures to be examined in a radiograph, to separate (segment) or classify the other data in the image (10,11,37,38). Panoramic radiographs are the most widely used radiological diagnostic tool in dentistry. It can be noted that the initial research on tooth numbering on panoramic radiography were presented when the first AI studies in oral and maxillofacial radiology were started (39). Bilgir et al. evaluated he diagnostic performance of an AI system based on a deep convolutional neural network method to detect and number teeth on panoramic radiographs.With an average sensitivity of 0.987 and a precision of 0.9945, the trained model had a high sensitivity comparable to that of an expert (Figure 5) (40).

Figure 5. An artificial ıntelligence approach to automatic tooth detection and numbering in panoramic radiographs (40)

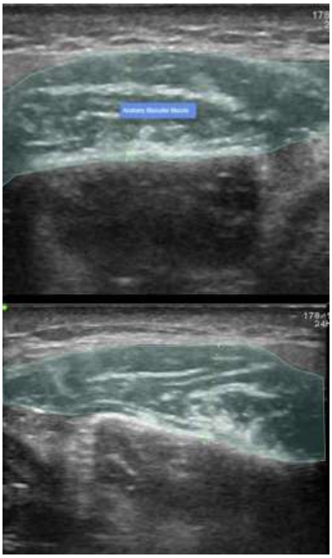


Several task-specific AI studies have started using radiography in recent years. Researchers stated that by using a CNN designed for the detection of benign tumors in the jaws called keratocystic odontogenic tumors and ameloblastomas on panoramic radiographs, they were able to create an algorithm that diagnoses conditions with a level of precision comparable to that of expert clinicians (41). In another study, a CNN model was created for the diagnosis of osteoporosis in panoramic radiographs. When the radiographs the algorithm identified were compared to those examined by experts, it was shown that the CNN accurately identified osteoporosis in each case (42). In their study examining the effectiveness and performance of artificial intelligence (AI) in the detection of osteoporosis, Lee et al. used deep convolutional neural network (DCNN) based computer aided diagnosis (CAD) systems for the detection of osteoporosis using panoramic radiographs and achieved quite high results, even when compared to qualified oral and maxillofacial radiologists (43).

Many maxillofacial cysts and/or tumors might be challenging for general practitioners to classify and diagnose. Even radiologists often struggle to make accurate diagnoses in difficult circumstances and must send patients for biopsies in order to make a certain diagnosis. The use of AI in the clinical setting to automatically diagnose lesions or tumors would be very beneficial. Moreover, Abdolali et al. (44) proposed a model based on asymmetry analysis to automatically segment radicular cysts, dentigerous cysts, and keratocysts using Cone Beam Computed Tomography (CBCT) which is an advancing area of imaging specifically designed for maxillofacial region and can provide three dimensional images of hard and soft tissue structures with lower dose of radiation (45-46). The proposed approach has been validated on clinical datasets with different jaw cysts. Using the proposed framework in the study , high true positive and low false positive values were obtained. Yet, developing a fully automated model that can identify cysts and/or tumors remains a challenge.

AI- based computer-aided detection and diagnosis are being utilized to improve the quality, efficiency, and affordability of US imaging, which has led to an increase in US acceptability for musculoskeletal assessments (47). Keser et al. aimed to evaluate the effectiveness of a deep convolutional neural network (D-CNN)-based AI system for masseter muscle detection and segmentation on US images (Figure 6) (48). The artificial intelligence deep learning model known as U-net provided the detection and segmentation of all test images, and when the success rate in the estimation of the images was evaluated, the F1, sensitivity and precision results of the model were 1.0, 1.0 and 1.0, respectively. The authors stated that AI shows promise in automatic segmentation of masseter muscle on ultrasonography images and this strategy can aid surgeons, radiologists, and other medical practitioners in reducing diagnostic time.

Figure 6. The images show the masseter muscle measurements performed on ultrasonographic images using AI Models (CranioCatch, Eskisehir- Turkey) (48)



In addition to radiology, another area where AI is used for diagnosis in dentistry is the detection of oral diseases. AI can help with early detection and reduce the mortality and morbidity linked to oral cancer. Moreover Aubreville et al. (49) employed DL to detect oral cancer. The specificity and accuracy of this approach were both 90%. Warin et al. (50) created an automated classification and detection model for oral cancer screening using CNN deep learning methods. DenseNet121 and faster R-CNN were used to generate the classification and detection models, respectively. The DenseNet121 and faster R-CNN algorithms were shown to have adequate potential for classification and detection of malignant lesions in oral photographic images.

To summarize, it is truly possible to make accurate diagnoses and give correct suggestions thanks to the recent, rapid development of AI technology specifically designed for dental professionals. At present, although AI methods are improving enough to make radiological diagnosis that will strengthen the dental profession, the development of the limits of use also gains importance.

AI in Oral and Maxillofacial Surgery

In order to prevent possible complications before the surgical operation is performed, detailed detection of anatomical landmarks can be made with AI algorithms. In this way, it is possible to preserve important anatomical structures and to complete the operations in a shorter time (3,37). Using CBCT images, Orhan et al. (51) examined the accuracy in identifying impacted third molars using an AI model. The AI model performed with 86.2% accuracy in determining the link of these teeth to anatomical structures. Another research used a deep convolutional CNN on panoramic radiographs to assess the complexity of third molar extractions. Success rates in detecting its connection to the ramus were 82.03%, 90.2%, and 78.9%, respectively (52). In addition, postoperative edema following tooth extraction has been predicted using AI technology. In order to predict postoperative facial edema following the extraction of impacted mandibular third molars, Zhang et al. (53) created an AI model. The model performed well and had a 98% accuracy rate. In another aspect, Kim et al. (54) used five alternative machine learning algorithms based on medication and C-terminal telopeptide (CTX) level values to determine the likelihood of bisphosphonate-related osteonecrosis developing following tooth extraction. The study revealed that machine learning, particularly the random forest model (97.3%) and ANN (91.5%), performed better than the traditional technique.

One of the more challenging problems for dentists is the diagnosis and treatment of temporomandibular joint (TMJ) diseases (37). An artificial neural network model was developed for a research with the goal of identifying internal TMJ pathologies from normal joint structure (55). To identify anterior disc displacements with and without unilateral or bilateral reduction, the model has been trained and evaluated. Although the model's sensitivity and specificity values for each instance are not high, it has been suggested that by expanding the data set, the model can be used as a supporting system for clinical diagnosis.

AI in Periodontology

Periodontal diseases are characterized by inflammation of the periodontium and can lead to tooth loss if left untreated (3). Various studies have been conducted on AI and DCNN applications in periodontology. Using 1044 periapical radiography pictures, Lee et al. (56) employed a CNN method to identify periodontally risky teeth, classifying them as healthy, moderate, and severe. The lowest and highest accuracy were computed independently for the mandible and maxilla, and they came out with 73.4% and 82.8%, respectively. The authors claimed that their CNN approach appeared to have a lot of promise because it accurately predicted the identification of teeth with periodontal insufficiency. Moreover, Alalharith et al. (57) reported that the success rate in the automatic detection of periodontal disease in patients receiving orthodontic treatment was 77.1%. In another study, Cha et al. (58) evaluated alveolar bone loss by detecting implants on periapical radiographs with the AI model they developed and reported that there was no significant difference between the model and dentists. Therefore, they stated that the model can be used in the detection of peri-implantitis. Thanathornwong and Suebnukarn (59) used a faster regional CNN system to analyze periodontally compromised teeth from 100 panoramic radiographs. The authors reported that the proposed system could be used to quickly detect periodontally compromised teeth and sensitivity, specificity, and precision were reported to be 0.84, 0.88, and 0.81, respectively.

One of the early signs of periodontal disease is gingival inflammation. A study reported a classifier CNN model with intraoral photographs to detect gingival inflammation. The algorithm colors the gingival areas that it predicts to be inflamed by performing pixel-based segmentation in the photographs. Although sensitivity and specificity tests do not give sufficient results for clinical practice yet, it has been introduced as an application that can give a preliminary idea to patients and clinicians (60). In short, it can be clearly stated that AI offers great potential to use a CNN system on periodontal radiography images as a decision-support tool for dental professionals while making diagnoses and designing treatment plans.

AI in Orthodontics

Anatomical point detection, extraction-versus-non-extraction orthodontic treatment, skeletal classification, determining the growth and development period, and orthognathic surgery are just a few of the analyses that AI may be utilized for (3, 37,61). Xie et al. (62) evaluated the need for tooth extraction before orthodontic treatment on lateral cephalometric radiographs with AI algorithms and ANN model used was successful with 80% accuracy. Moreover Kunz et al. (63) reported that there was no significant difference in the results obtained in landmark detection between the AI model and the dentist. On the other hand, using lateral cephalograms, Yu et al. (64) demonstrated modified DenseNet that has been pre-trained with ImageNet weights. The accuracy of the model was 95.70% higher than that of five orthodontists. Using YOLOv3 on 1311 cephalograms, Park et al. performed landmark detection. With a 5% greater accuracy compared to top benchmarks, the model was successful in detecting 80 landmarks. Moreover, the use of attention-based networks in landmark identification has been intensively investigated (65). Successful results have also been obtained in orthognathic surgery planning with AI. Choi et al. (66) developed an AI model for the diagnosis of patients who will receive orthodontic treatment, both requiring and not requiring surgery, and the model showed a high performance of 96%.

AI in Restorative Dentistry

Several researchers have investigated at the use of AI in restorative dentistry. In order to accurately plan treatment utilizing clinical examples, Lee et al. suggested a machine learning technique based on a decision tree to evaluate the tooth prognosis. The accuracy of the model was 84.1% (67). Abdalla-Aslan et al. suggested a cubic SVM-based technique employing panoramic radiographs. The model may be able to identify and categorize dental restorations in order to improve patient health (68).

Cantu et al. (69) compared the performance of experienced dentists with the AI model they developed in the diagnosis of caries on bite-wing radiographs. In the study, the algorithm was found to have a significantly higher accuracy rate (80%) than dentists (71%). Askar et al. (70) performed the detection of white spot lesions in intraoral photographs with the DL method, and the system showed an accuracy of over 80%. Therefore it can be stated that DL supported AI models will be an effective caries diagnosis method in the coming years (2,3).

AI in Endodontics

Artificial intelligence algorithms for the identification of periapical disease and can benefit from the properties of periapical radiolucency (71). Models to classify the severity of periapical lesions in relation to the diagnosis of periapical disease were published by Carmody et al (72). A deep learning algorithm model can identify periapical radiolucencies on panoramic radiographs as precisely as 24 oral and maxillofacial surgeons, according to Endres et al (73). According to Orhan et al.'s findings (5), the AI system was able to accurately identify 142 out of 153 periapical lesions with a detection accuracy rate of 92.8%. The detection of cystic lesions has been done using artificial neural networks (74). Additionally, Flores et al. (75) established a methodology to separate granuloma from periapical cysts using CBCT images. It is valued highly in clinical practice because it allows periapical lesions to recover following root canal therapy without the need for surgery.

The efficiency of nonsurgical root canal treatment depends critically on an understanding of the various types of roots and root canal systems. An automatic, three-dimensional teeth segmentation using the CNN method was demonstrated by Lahoud et al.(78). The researchers showed that artificial intelligence outperformed human operators while working substantially quicker in a clinical reference evaluation of 433 cone-beam computed tomographic segmentations of teeth.

Conclusion

Throughout the past ten years, artificial intelligence has made a significant contribution to several subfields of dentistry. AI has a wide range of functions and applications in the health-care industry. The continuous use of AI in dentistry will help researchers and clinicians combine several fields of expertise and enhance patient care. Nonetheless, it is crucial to be mindful of any mistakes that might be made when using AI systems to evaluate data. Nowadays, it makes sense to merge AI technology with traditional approaches in order to reduce output mistakes.

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