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A primer and overview of the role of artificial intelligence in oral and maxillofacial radiology

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INTRODUCTION

Many have read or heard the term "artificial intelligence (AI)," but what does it mean, and more specifically for the purposes of this issue, what does it mean for the discipline of oral and maxillofacial radiology (OMR) both in the present and future of dentistry? Uses of AI are ubiquitous around the world in such varied applications as global positioning system maps, predictive aging technology, music sites, and character reconstruction from decades-old movies, to name a few. AI is so pervasive in contemporary society that it affects many aspects of human activity. Oral and maxillofacial radiology and dentistry are no different, so one may ask, "Why is it so important?"

This special focus issue features the use of AI in the practice of OMR and dentistry in current research that addresses diverse applications for both the present and future. The purpose of this article is to briefly describe the concepts of AI in a tutorial fashion, summarizing current knowledge and research principles with an eye to future applications. The article will provide a definition of AI and its application in the form of machine learning (ML) and, more specifically, deep learning (DL), a subset of ML, followed by a discussion of the appropriate methods to be used in AI research. Currently, AI research usually involves DL, and most of the studies in this issue use DL methods of artificial neural networks, such as convolutional neural networks (CNNs), but often substitute the term "artificial intelligence" for it. Going forward, when the term "AI" is used, it should be understood that almost all its applications mentioned herein are based on DL technology. In fact, throughout this paper, "DL" could be substituted for "AI."

A general overview of the current state of AI in applications germane to OMR and dentistry is presented in the following sections. No overview would be complete without reviewing some of the key issues in DL research and development as a guide for AI investigators to follow. Finally, the article will address the question, "Where do we as oral and maxillofacial radiologists go from here?"

AI can be defined as the theory and development of computer programs capable of performing complex tasks traditionally accomplished using human intelligence.[1] After AI was first introduced for radiology applications in the 1960s, its capability was limited until the introduction of DL and artificial neural networks in the 1980s. DL can be considered a subbranch of AI that uses multiple interconnected and layered networks to learn from data.[2] The introduction of CNNs has generated promising results in the medical field, serving as an aid for diagnosis and treatment decision-making for health care professionals.

Schwendicke et al. further refined the definitions of AI, ML, and DL, explaining, "The term 'artificial intelligence' refers to the idea of machines being capable of performing human tasks. A subdomain of AI is machine learning, which 'learns' intrinsic statistical patterns in data to eventually cast predictions on unseen data."[3] The authors described DL as an ML technique using "multi-layer mathematical operations for learning and inferring on complex data like imagery."[3] Most studies in this issue used CNN methods, which simulate human neuronal architecture to process digital signals, as the main tools for DL. In summary, Chartrand et al. stated, "The key aspect of DL is that these features are not designed by humans but automatically extracted and learned from the raw data (such as pixels of images)."[4]

GOALS OF AI IN OMR AND DENTISTRY

Mayo and Leung posited 4 goals for AI: improving radiologist performance, saving time, seamlessly integrating into the workflow, and having negligible incremental costs.[5] In OMR, the goal is not to replace the radiologist or dentist as the decision maker. AI should be aimed at aiding the radiologist or dentist in the process of interpretation and diagnosis but not to make the final diagnostic or treatment planning decisions. Such decisions should be made by humans, not machines. The goal is to indicate areas of concern for the clinician to evaluate and interpret, leading to some type of management decision. In essence, AI should mean "augmented intelligence."

The process of interpreting and managing radiographic information involves 3 components. First, the clinician must see the disease or abnormality. This is

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no small task for many applications, such as the detection of carious lesions, where sensitivities are generally low.[6,7] Second, based on radiographic features, the clinician should understand the nature of the lesion (e.g., whether benign, malignant, inflammatory, or other classification of disease). In other words, the clinician must decide on a category of disease or a differential diagnosis. Finally, the clinician must decide how to manage the radiographic information and select a course of action, such as referring for a biopsy, producing a radiology report, or monitoring the patient. In the process of seeing, understanding, and managing, AI is most appropriate for seeing, that is, identifying a potential abnormality. AI can also aid in understanding the potential lesion and may even assist in the final decision but should not be the decision maker. In other words, AI detects, and the clinician diagnoses.

In summary, the overall goal of AI practice and research should not be to replace radiologists and dental clinicians but rather to aid their interpretive performance. The goal of AI research, therefore, should not always be aimed at the question, "How good is AI vs clinicians?" but rather, "How can AI help clinicians interpret the nature of abnormal findings?" There is a role for standalone testing of AI in which the diagnostic outcomes measures of the AI model are compared to those of clinicians in the initial stages of research. However, the end goal should always be to improve the clinician's diagnostic outcomes and not serve as a substitute for clinician decision-making. In accordance, testing of AI software should include a standalone portion followed by measurement of the effects of AI on observer performance. This is one reason that many investigators and clinicians refer to AI as computer-assisted diagnosis or augmented intelligence.

HOW DL WORKS: TRAINING, REFERENCE STANDARDS, VALIDATION, AND TESTING

Neural networks, which are the bases of DL, are composed of multiple layers, each performing a discrete task in an iterative fashion, resulting in a program that teaches itself how to learn. The first step in the process is the creation of a training data set. A large amount of annotated data, in this case from diagnostic imaging, is provided to a DL computer program, which then learns to detect patterns in the data in a training session specific to the task. Most importantly, the program must be told what it is looking for. This is usually accomplished by presenting manifold images of the object to be identified, which may number in the hundreds or thousands.[5] As an example, imagine that one wants to train a computer to recognize a certain kind of bird. A training data set composed of thousands of bird images is fed into the CNN. The program is then presented with a picture of a bird and correctly identifies it as a bird. However, to make the program more generalizable, many diverse types of birds must be shown, each in sufficient numbers. If shown only an eagle, the program will be able to recognize eagles but few other types of birds. Similar training data set requirements are needed to train a program to recognize the radiographic features of caries, apical radiolucencies, periodontal bone loss, or other lesions of the jaws and dentomaxillofacial complex.

After training and before testing, there is an intermediary step known as validation, which ensures that the model is ready for testing. Typically, the validation set is approximately the same size as the testing set. Validation of the training data set is vitally important. Referring to the previous example, when teaching a DL program to recognize birds, the training set must use images of a true bird, not a bat or pterosaur. Similarly, when training a DL program to recognize dental disease, true examples of disease must be presented to the system. This requires a reference standard that is used to correctly label true examples of the disease.

Reference standards for training a program to identify the radiographic signs of disease fall into 3 types. The most commonly used reference standard is a consensus panel of experts, such as a panel of oral and maxillofacial radiologists. The most robust type of consensus panel is one that uses the Delphi method, by which the experts are surveyed to arrive at a group opinion or decision. The experts respond to several rounds of questionnaires, and the responses are aggregated and shared with the group after each round in an iterative manner.[8] To date, most AI studies have not used the Delphi method due to the amount of time it requires to evaluate hundreds or thousands of images. In addition, for best results, Delphi methods require an appropriate panel size and diverse representation of members from different specialties and geographic distribution, which are often difficult to attain. In using a consensus panel, each image in the training data set is annotated such that the program knows that the digital characteristics within the annotation constitute the radiographic characteristics of the lesion to be identified. For example, in order to train a program to identify carious lesions, each radiograph in the data set must contain a box or circle (or some form of annotation) around either a lesion or an area with no lesion to serve as a control. The annotated and control radiographs are then presented to the program for training.

The use of cone beam computed tomography (CBCT) volumes as a reference standard for detecting lesions on 2-dimensional (2D) radiographs can also be employed. CBCT is not a true gold standard but arrives closer to the truth than a consensus panel for some detection tasks, such as the detection of periapical lesions. The most reliable reference standard is histologic or microCT interpretation of lesions, but the situations where they can be applied are limited.

Currently, most AI programs and research are aimed at identifying potential diseases or abnormalities by radiographic features and are not intended to diagnose diseases. To be identified, such lesion features must be different in size and density. In addition, an effective and generalizable DL program designed to detect disease—caries, for example—must be shown examples of caries from multiple imaging systems, such as intraoral direct digital and photostimulable phosphor bitewing, periapical, and panoramic radiographs. The training data examples should include a variety of manufacturers' systems from a wide variety of dental practices. It is easy to see that the requirements for training a computer to recognize diseases or abnormalities are not insignificant. Unfortunately, the relaxation of these requirements has resulted in a lack of methodological rigor, thus slowing down the development and adoption of AI systems for dentistry.[3]

Following the construction of the training data set, the system must be challenged with an unannotated testing set, usually smaller than the training data set. The test data set consists of examples of the diseases to be identified as well as controls with no evidence of disease. The training and testing data sets must not be mixed. The test determines the degree to which the DL program aids the clinician in diagnostic effectiveness.

OUTCOME MEASURES

The predictions made by DL systems to assist clinicians in the decision-making process must be evaluated for their value. Outcome measures that are often used are accuracy, recall (sensitivity), specificity, precision or positive predictive value (PPV), F1 score, and area under the curve (AUC) generated by receiver operating characteristic analysis. Accuracy, the probability that an individual item will be correctly classified by a test, is the ratio of true positive and true negative diagnoses to all diagnoses. Accuracy is often confused with other terms in the assessment of diagnostic imaging for evaluating the validity of outcomes. Recall (sensitivity) is the number of correct positive predictions divided by the total number of actually positive cases (i.e., true positives and false negatives). Specificity is the ratio of true negatives accurately diagnosed by the test divided by the total number of all actually negative cases (true negatives and false positives). Precision or PPV is the probability that patients with positive test results truly have the disease being tested. The F1 score, which quantifies the degree to which a test can effectively identify positive cases while minimizing false positives and false negatives, is derived from recall and precision calculations. AUC is often used to calculate the probability of a test correctly discriminating between the presence and absence of disease.

APPLICATIONS OF AI IN OMR

The applications of AI for OMR and dentistry are many and varied. What follows is a general but not complete overview of current applications of AI in published investigations. Topics include dentoalveolar applications such as charting teeth and identifying signs of caries, periodontal disease, and endodontic periapical lesions, followed by applications for orthodontics, oral pathology, and temporomandibular joint (TMJ) disease. A discussion of potential applications related to quality assurance is also included.

Dental charting

Several AI and computer-assisted diagnosis tools aimed at tooth detection and labeling have recently emerged. The inspiration behind the development of these tools relates to the prospects of saving time and improving workflow and accuracy. Inaccuracy in charting teeth is still an issue of concern in dentistry.[9] In a study using a DL model for tooth identification and numbering in panoramic radiographs, Tuzoff et al. found that this technique had a mean recall of 0.987 and precision of 0.9945, a result that matched dentists' performance.[10] In a study using a type of DL to correctly identify teeth, Zhang et al. obtained favorable results, with a recall and precision of 96.1% and 95.8%, respectively.[11] When Chen et al. used DL to detect and label teeth on 1,250 digitized dental periapical radiographs, they obtained a detection precision of 90% compared with human experts and a 71.5% precision in tooth numbering.[12] These results are encouraging, but more studies of DL as an aid in improving clinician accuracy in tooth charting are needed.

Detection of dental caries

In a study using DL for caries detection on periapical radiographs with expert opinions serving as the reference standard, Lee et al. found that the overall accuracy for caries detection in the premolar and molar sites ranged from 82% to 89%, depending on the location. The authors concluded by stating, "Findings from the present study suggest that a DL algorithm can provide considerably good performance in detecting dental caries in periapical radiographs."[13] In a study using histologic sectioning as the reference standard, Valizadeh et al. discovered that DL was able to diagnose 60% of enamel caries and 97% of dentinal caries, but they did not report the specificity.[14] In a different type of investigation, Schwendicke et al. conducted a cost-effectiveness analysis of using a DL tool for the detection of proximal caries. Finding that AI saved money and provided higher effectiveness, they concluded that AI has the potential to improve health care at lower costs. The research protocol of their study, one of the few investigations of AI as an aid in improving clinician performance, assumed that early lesions would be treated non-restoratively.[15] The aforementioned studies are similar to many others in the literature. Most current research applying DL tools for caries detection has used clinicians as a reference standard in standalone studies.

Periodontal disease

Most investigations that focused on periodontal disease detection have employed standalone studies, with clinician panels establishing the reference standard. Many of these studies were based on panoramic radiographs, with a few using the more standard intraoral radiographs for detecting periodontal bone loss. Using a DL program, Krois et al. observed a discrimination ability, sensitivity, and specificity similar to those of dentists for assessing periodontal bone loss on panoramic radiographs with improved workflow and time savings.[16] After applying DL to the detection of periodontal bone loss on panoramic radiographs, Kim et al. concluded that DL could be a useful adjunct in performing diagnoses. Their study was one of the few that did not use a pure standalone design.[17] One recent investigation employing intraoral radiographs to train and test a DL model in the prediction of periodontally compromised teeth and the need for extractions yielded promising results, with diagnostic accuracy of 81.0% for premolars and 76.7% for molars. The accuracy of predicting the indications for extractions was 82.8% for premolars and 73.4% for molars.[18]

Endodontic applications

As with most research, studies focusing on endodontic applications have been standalone investigations comparing AI to dental clinicians. When Ekert et al. applied DL to panoramic images, they observed a satisfactory ability to detect apical lesions. With the consensus of 6 examiners serving as the reference standard, sensitivity and specificity were 65% and 87%, respectively, with an AUC of 85%. The authors concluded that "the application of neural networks may assist dentists in reliably and accurately detecting apical lesions."[19]

Endres et al. employed DL for the detection of periapical radiolucencies on panoramic radiographs using a clinically validated reference standard to perform differential diagnosis of the lesions, including periapical granulomas, periapical cysts, and tumors. They found that the DL algorithm achieved a better performance than 14 of 24 oral and maxillofacial surgeons within the cohort. Their results included an F1 score of 0.58 (±0.04), resulting from a sensitivity (recall) of 0.51 (±0.05) and a mean PPV of 0.67 (±0.05). Although these results are not exceptionally high, they indicate that the algorithm has the potential to aid oral surgeons in detecting periapical radiolucencies on panoramic radiographs.[20] Setzer et al. obtained robust results when they used a DL algorithm for the automated segmentation of CBCT images and the detection of periapical lesions, with an accuracy of 0.93 and a specificity of 0.88.[21] When Orhan et al. used DL to detect apical pathosis on CBCT using 153 periapical lesions obtained from 109 patients, they found that the AI system was able to detect 142 of a total of 153 periapical lesions (92.8%) correctly.[22]

Orthodontic applications

In a study using DL, Jung et al. concluded that there were small differences between human experts and the predictions of an AI system in assessing the need for extractions for orthodontic purposes based on cephalometric radiographs.[23] The authors concluded, "By mimicking the decision-making of experienced experts, the artificial intelligence expert system could be a reference for less-experienced practitioners." Hwang et al. found that AI was as accurate in the identification of 80 cephalometric landmarks as trained orthodontists; the mean detection error size between humans and AI was less than 0.9 mm and not clinically significant.[24] Again, as with other studies, the aim was to compare the results of AI with the judgments of dental clinicians.

Pathoses of the jaws

Most AI research to date has featured the identification of radiolucent lesions on panoramic radiographs in standalone studies. Ariji et al. used DL to automatically detect and classify radiolucencies in the mandible on panoramic radiographs in a study incorporating histologically verified lesions of 10 mm or greater in the mandible. The 5 types of lesions included ameloblastoma, odontogenic keratocyst, dentigerous cyst, radicular cyst, and simple bone cavity. They found a detection sensitivity of 88%, which, despite the use of a limited validation data set, indicated that radiolucent lesions of the mandible could be detected with high sensitivity using DL.[25] In an investigation of 3 types of cystic lesions (odontogenic keratocyst, dentigerous cyst, and periapical cyst) using panoramic radiographs and CBCT, Lee et al. found that the pre-trained model using CBCT images as a reference standard yielded good diagnostic performance (sensitivity = 96.1%, specificity = 77.1%, and AUC = 0.914). The results were significantly better than those achieved by other models using panoramic images.[26] Significantly, both studies[25,26] used more robust reference standards, such as histologic verification or CBCT volumes, than the use of a consensus panel.

The importance of using AI technology for identifying jaw lesions in CBCT scans cannot be overemphasized, as the purchase and use of CBCT systems are increasing rapidly. It is assumed that more CBCT volumes will be obtained, and many dentists are not properly trained or may not take the necessary time to review their CBCT volumes. This means that if these trends continue, most dentists will own or use CBCT systems in the not-too-distant future, much like panoramic units today. They will need the help that DL can provide in identifying and classifying abnormalities. There are not enough oral and maxillofacial radiologists to interpret all or even most CBCT volumes obtained in dental clinics; thus, AI will be helpful in identifying potential lesions of the jaws that can then be referred to OMRs for an interpretive report. [27]

TMJ applications

TMJ assessment with AI has not been investigated as frequently as other applications to date. Most studies are similar to that of Lee et al.,[28] whose objective was to develop a diagnostic tool to automatically detect TMJ osteoarthritis from CBCT scans. The average accuracy, recall, precision, and F1 score over the 2 test sets were 0.86, 0.84, 0.85, and 0.84, respectively. The authors concluded that detection from sagittal CBCT images is possible by using a deep neural network model.

Image quality improvement

Another application of importance in diagnostic imaging is the improvement of the image quality of 2D images and 3D volumes. Motion artifacts in CBCT are especially problematic due to the single-rotation nature of basis-image acquisition. Applying CNNs in an effort to reduce motion artifacts, Park et al.[29] used resolution, contrast, and noise in assessing performance. When they compared low-resolution images enhanced by the DL CNN to the standard high-resolution images, they found no differences. The authors concluded that the DL method could be useful for CT image quality improvement.[29] In addition to reducing motion artifacts in CT imaging, DL using CNN is being explored as a means of reducing metal artifacts. Improvements in computed root mean square error and the structural similarity index have been documented.[30]

ASSESSMENT OF THE ROLE OF AI IN OMR AND WHERE WE GO FROM HERE

Nagi et al. concluded that AI has promise for the interpretation and accurate localization of landmarks and characterization of bone architecture in the assessment of 2D and 3D images. They also concluded that radiologists should be trained in the use of AI systems and apply them to their work.[31] This author agrees with their assessment and notes that knowledge of AI in theory and practice will most likely be added to accreditation requirements for OMR programs.

From the overview above, it can be seen that AI, and especially DL, will play a significant role in shaping the future of OMR research, training, and practice. Results thus far are promising but limited. Much research needs to be performed before AI is integrated into the clinical practice of dentistry and OMR. The current limitations of most research thus far have been the use of relatively small numbers of training images, a lack of diversity in imaging equipment type and manufacturers' products, and a limited number of practices as sources of training images.

In addition, the lack of "ground truth" reference standards, such as histologic examination and, to a lesser extent, CBCT, may be a limiting factor. Practically speaking, most AI research relies on consensus panels for producing reference standards. Where possible, consensus panels should not be limited to licensed dentists but, in most cases, include OMRs and other specialty-trained dentists, depending on the diagnostic task. The Delphi method should be used as a reference standard where feasible.

The aforementioned limitations currently restrict the generalizability of AI systems. In this author's view, not enough studies are evaluating AI as an aid in improving clinician performance. Future research should focus not on how good AI is as a standalone system but rather on quantifying how well it helps the dentist in achieving optimum diagnostic performance for improvement in patient care. In other words, AI should be a "rising tide that lifts all boats." This should be the true measure of an AI system. In the near future, AI will be an integral part of OMR and dentistry. Now is the time for all general dentists and dental specialists to learn about AI and how to apply and use it appropriately for the purpose of improving diagnosis and, ultimately, patient care.

DECLARATION OF INTEREST

D.A.T. has consulted for Denti.AI.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Donald A. Tyndall: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Writing – original draft, Writing – review & editing.

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