Deep learning and computer vision: Two promising pillars, powering the future in orthodontics

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Currently, advances and affordability in digital data have increased the demand for expedite and automate several diagnostic and clinical tasks. In this regard, Artificial Intelligence is an extraordinary tool destined to support diagnosis, treatment plan and prognosis and to monitoring the progresses of orthodontic treatments. This paper is intended to help orthodontists in getting familiar with and to provide a breakdown of several of the pioneering applications of AI with special regard to Deep Learning and Computer Vision in orthodontics for continued innovation. (Semin Orthod 2021; 27:62–68) *© 2021 Published by Elsevier Inc.*

Introduction

The introduction of Artificial Intelligence (AI) into the medical field has taken up the challenge to support assessments for diagnosis, therapy, prognosis, and patient monitoring.

While Hollywood movies and science fiction novels, portray artificial intelligence as androids taking over the world, the current evolution of AI technologies isn't that scary. Instead, artificial intelligence has evolved to provide many specific benefits across different fields.

Artificial intelligence (AI) is the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. Thus, AI itself is a general term that describes computers mimicking human intelligence and computer systems able to perform tasks normally requiring human intelligence.

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The term is frequently applied to the project of developing systems endowed with the intellectual processes characteristic of humans, such as the ability to reason, have visual perception, discover meaning, generalize, or learn from past experience.

"Machine Learning" (ML) is a subset of AI (Fig. 1), and it was originally described as a program that learns to perform a task or makes a decision automatically from data, rather than having the behavior explicitly programmed. ML is characterized by mathematical and statistical techniques enabling machines to improve their abilities by experience. ML methods are categorized on the basis of the models and algorithms used.[1] Methodological approaches to learning include Supervised learning, Unsupervised learning, Semi-supervised learning, Reinforcement learning, and Self-learning. Performing machine learning involves creating a model, which is trained on some training data and then can process additional data to make predictions. Various types of models have been used and researched for machine learning systems, these include Artificial Neural Networks (ANNs), Decision Trees, Support Vector Machines (SVMs), Regression analysis, Bayesian networks, and Genetic Algorithms (GA).

However, the two main types of ML methods that are currently used in healthcare are supervised and unsupervised learning. In Supervised learning, the machine is trained using data for

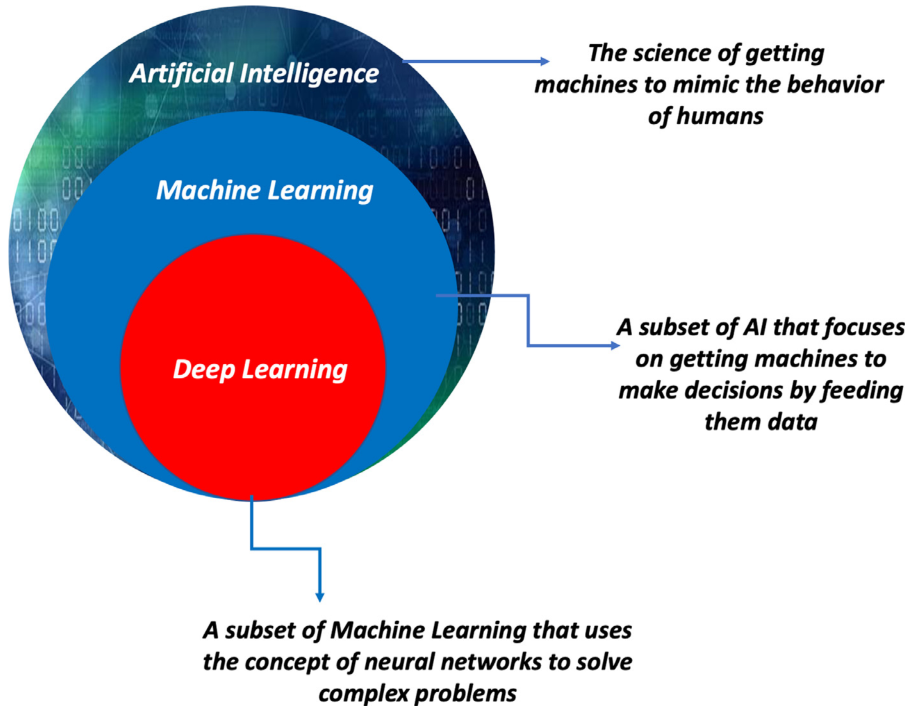

Figure 1. Artificial intelligence and its subsets.

which ground truth is available and it is well "labeled". It means some data is already tagged with the correct answer. Supervised learning is typically used in the context of classification.

Unsupervised learning, on the other hand, does not make use of label outputs, it is a machine learning technique where a model does not need to be supervised. In fact, the model is allowed to work on its own to discover information by detecting inherent structure or regularities in the data. It deals with the unlabeled data, and it is commonly used for tasks such as clustering or categorization.

Deep learning is a subcategory of machine learning even though artificial intelligence, machine learning, and deep learning are three terms often used interchangeably to describe software that behaves intelligently. However, it is useful to understand the key distinctions among them. You can think of deep learning, machine learning and artificial intelligence as a set of Russian dolls nested within each other, beginning with the smallest and working out. Deep learning is a subset of machine learning, and machine learning is a subset of AI, which is an umbrella term for any computer program that does something smart (Fig. 1).

Machine learning and deep learning are both responsible for the recent, major breakthroughs in Computer Vision technology. This is one of the most powerful and compelling types of AI which everyone has almost surely experienced in any number of ways without even knowing. Computer vision focuses on replicating parts of the complexity of the human visual system and enabling computers to identify and process objects in images and videos. Typical computer vision tasks include image classification, segmentation of areas of interest, object detection, and recognition. Until recently, computer vision only worked in a limited capacity. Thanks to advances in artificial intelligence and especially innovations in deep learning, that have reshaped the architectures of classical ANNs, the field has been able to take great leaps in recent years and has been able to surpass humans in some tasks related to detecting and labeling objects.

One of the driving factors behind the growth of computer vision is the amount of data that can be generated today that is then used to train and make computer vision better allowing models to use thousands of rich predictor variables.[2] Computer vision is today assisting an increasing number of doctors to better diagnose their patients, monitor the evolution of diseases, and prescribe the right treatments. The technology not only helps medical professionals to save time on routine tasks and give more time to the patients. The implications of computer vision for medical use based on tasks such as medical imaging analysis, predictive analysis, or healthcare monitoring suggest a host of benefits to the healthcare industry.

The emerging field of computer vision focuses on training computers to replicate human sight and the understanding of objects in front of it. To accomplish that, computer vision takes advantage of artificial intelligence algorithms that process images. The goal of computer vision in healthcare is to make a faster and more accurate diagnosis than a physician could make. Currently, the most widespread use cases for computer vision and healthcare are related to the field of radiology and imaging. AI-powered solutions are finding increasing support among doctors because of their diagnosis of diseases and conditions from various scans such as X-ray, and MR, or CT.

Areas that may benefit from the application of Artificial Intelligence in the medical field are diagnosis and treatment planning, personalized treatment, clinical trial research, and smart electronic health records. In most of these fields, Deep Learning and Computer vision are involved. The aim of this paper is to provide a breakdown of several of the pioneering applications of AI with special regard to Deep Learning and Computer Vision in orthodontics for continued innovation.

Diagnosis, treatment planning, treatment outcomes and growth pattern

The most important parts of orthodontic treatment are to determine the treatment plan, outcomes, and monitoring patients.[3] AI can automate the manual work and speed up the process of diagnosis, treatment planning, treatment outcomes and growth pattern.[4] In this respect, AI is particularly helpful in areas where the diagnostic information a doctor examines is already digitized.

Currently, advances and affordability in digital data have recently increased the demand for the orthodontic profession to automate cephalometric analysis and several diagnostic tasks that were once carried out by the clinician, among these: cephalometric analysis, segmentation of anatomical bone-structure from cone beam computed tomography (CBCT) images and treatment plan decision. Several attempts to automate cephalometric analysis have been carried out,[5] both on 2D images (lateral cephalometric x-ray) and on 3D image (CBCT), with the aim to reduce the time required to obtain analysis, improving the accuracy of landmark identification, and reducing the errors due to clinicians' subjectivity.[6-8] For 20 years now, automatic identification of landmarks has been undertaken in different ways that involve computer vision, artificial intelligence and deep learning techniques, with increasing reliability and accuracy of landmarking.

Presently, the trained AI algorithm is capable of analyzing and automatically annotate cephalometric landmarks on radiological images in a fraction of a second, even when used on a standard personal computer, with comparable precision to experienced human examiners (which is deemed to be the current gold standard). However, the usefulness of a 3D cephalometric analysis based on 2D cephalometric measurement and landmarks has been questioned (for example, see Fig. 2), thus searches using AI and computer vision on this field have slowed down. Besides, more accurate and reliable methods to perform cephalometric superimposition,[9] than those based on landmarks, have been introduced (i.e. voxel based superimposition and surface to surface matching) resulting in that cephalometric landmarking is outdated.

Recently, machine learning and deep learning techniques have been applied for fully automatic segmentation of maxillary and mandibular bones, upper airway, and for skeletal bone age assessment[10-12] In 3D medical imaging, segmentation is defined as the construction of 3D virtual surface models to match the volumetric data[13]. In other words, it means to separate a specific element (for example the maxilla, the mandible and the upper airway) and remove all other structures of non-interest for better visualization and analysis, this allows the evaluation of the size, shape, and volume of the anatomic structure already segmented[14-17] (Fig. 2). Segmentation of medical image data is getting more and more important over the last few years and is mainly used for diagnosis, treatment outcomes (inter-timing assessments), and surgical planning.

Manual segmentation seems to be the method with the greatest accuracy and it is based on the performance of one clinician. In the manual

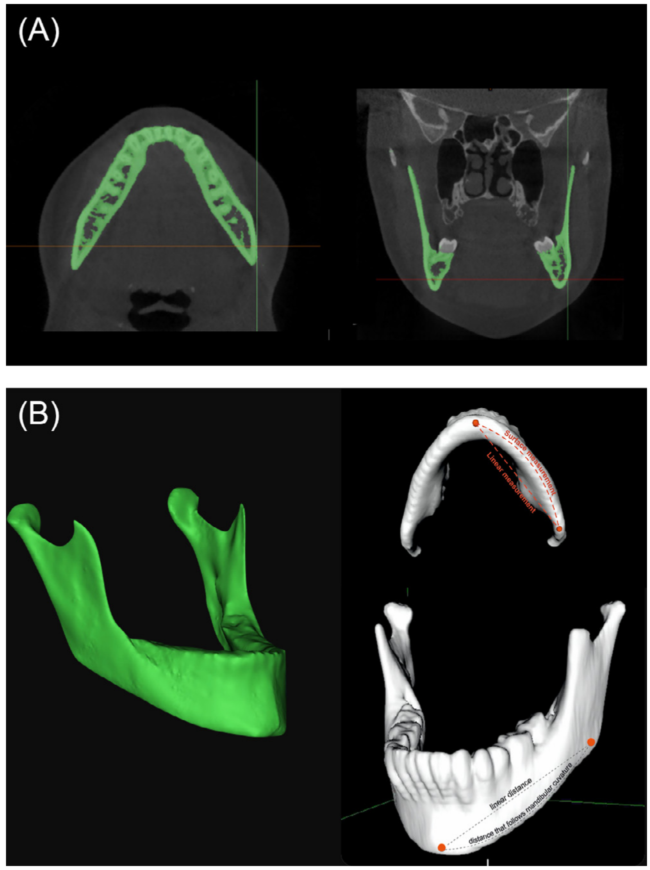

Figure 2. Segmentation mask of the mandible (A) and 3D rendered models obtained with manual (green) and fully automatic (gray) segmentation methods (B). The two models perfectly overlap. Also, see how 2D linear measurements from conventional cephalometric dataset cannot accurately detect the dimension of 3D structures, in this case the gonion-menton distance.

approach, the segmentation is performed slice by slice by the user. The software then combines all slices to form a 3D volume.[13] However, manual segmentation is time consuming, tedious, and requires expertise. Thus, automated methods are desirable. Consequently, completely fully automated systems to segment any structure from CBCT images have been advocated and experimentally developed. Recently, the application of AI, through its deep learning paradigm, has shown very promising results in automated segmentation of anatomical structures from CT and CBCT. In particular, convolutional neural networks (CNNs)[18] have led to a series of breakthroughs in CBCT segmentation,[19] especially when compared to previous methods employing general hand-crafted features, thanks to learning task-specific features directly from data. Practically, with fully automatic segmentation the clinician does not need to select boundaries and threshold values nor to trace any anatomical structure, as these steps are carried out automatically by the software, the clinician needs only to upload the DICOM file. This is revolutionary in "digital" clinical practice. Fig. 2 (A,B) shows two examples of automatic segmentation of the mandible based on convolutional neural networks (CNNs). Once the mandible is segmented and reconstructed in a 3D fashion, volume, area and surface measurements can be obtained.

Another clinical application of machine learning and deep learning is the possibility to automatically segment the sino-nasal cavity and the pharyngeal airway in CBCT scans (Fig. 3).[12] In this regard, the upper airway has always been an area of interest in orthodontics for a long time, with topics such as the relationship between facial type growth and development, and the

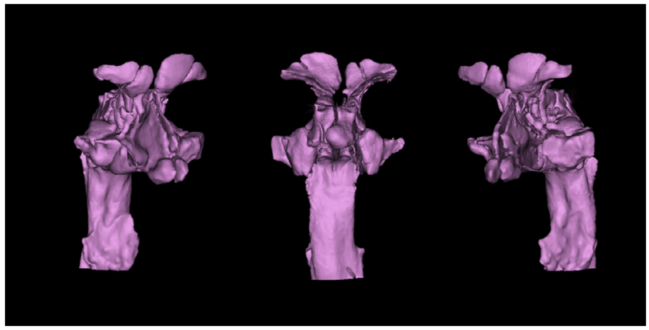

Figure 3. Fully automatic segmentation of the sino-nasal cavity and pharyngeal airway based on convolutional neural networks.

clinician's potential to modify the airway.[20] There is also a trend in orthodontics to use patients' airways quantitative data pre- and post-treatment to determine the effects of a particular intervention on the airway dimensions.[21] Furthermore, a future goal of fully automatic segmentation from CBCT will be the 3D reconstruction of teeth and root from CBCT images, with the advantage to plan orthodontic customized therapy, especially for complicated cases (Fig. 4).

For orthodontic treatment planning, decision-making expert system (ES), based on machine learning and artificial neural networks (ANN) have been designed.[22] This ES not only can assist less-experienced orthodontists and students in learning but also can help patients obtaining a clear understanding of their treatment plans. As far as treatment outcomes are concerned, AI has been applied for the prediction of soft tissue treatment outcomes.[4] In this regard, ANN was used to forecast the change in lip curvature after orthodontic treatment with or without extractions and treatment outcomes in Class II and Class III. AI has been applied also for the classification of growth patterns with a success rate of 64% in classifying good or bad growers based on the changes in their sagittal relationships.[23]

Deep learning is also involved in the field of personalized treatment. Medicine is undergoing a revolution that is beginning to lead a proactive P4 medicine that is predictive, preventive, personalized and participatory. The need for personalized treatment and a P4 approach has been felt also in orthodontics, as being discussed during the Consortium for Orthodontic Advances in Science and Technology (COAST) symposia. These meetings provided a series of highly interactive workshops on the topic of 'Personalized and Precision Orthodontic Therapy.[24–26]

However, the employment process of AI in orthodontics is being delayed compared to other

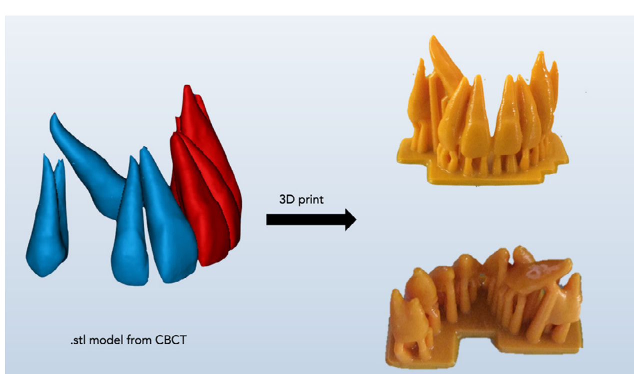

Figure 4. CBCT-derived 3D model and prototyped model of a maxillary arch with a palatally displaced impacted canine. By using these models, it is possible to effectively customize the orthodontic therapy, in particular the design of the orthodontic appliance, basing on specific biomechanical considerations.

medical fields as it is supported by scarce scientific evidence. In this regard, less than 200 papers appear on Pubmed using "artificial intelligence" and "orthodontics" as strategy string research, thus further studies and prompt efforts are warmly encouraged to address this issue.

Conclusions

Artificial intelligence is already part of our everyday lives. Whether we are using our smartphones, surfing the internet, buying products online, using navigation, or listening to songs on our favorite music streaming service, AI is impacting our choices in one way or another.

Maybe, the future of orthodontic practice, at least for simple clinical cases, will no longer be driven by appliances but by Artificial Intelligence, but before it becomes a reality several problems should be faced and overcome. Serious concerns regarding licensure, liability, patient confidentiality, and un-monitored do- it- yourself orthodontic (DIY) treatment remain to be addressed.

Actually, classic diagnosis can be interpreted as an interaction between a doctor and a patient, where the doctor identifies the disease and suggests a treatment, and the patient decides if she/he accepts or rejects the medical opinion. This paradigm could be transformed by the development of deep learning: in such a case, the patient will give her/his personal data to a machine, which will produce, as an output, a diagnosis and best treatment. However, this scenario involves several issues, which reduce the possibility of a complete automatic data analysis process. Secondly, another issue consists in the contrast between the natures of a human and a machine. A machine provides a diagnosis of a disease considering only a rational component, while a patient takes a decision considering both a rational and irrational component. A possible solution to alleviate these issues is to introduce a new medical paradigm, where the doctor is helped by the machine in providing a patient with a precise diagnosis.

The best results are thus realized when ML works in support of health personnel, acting as a "second set of eyes", providing a means of cultural integration between humans and smart machines, thereby avoiding conflict, basically irrelevant, between cognitive, human and artificial methods, in short being more "intelligent".

Many challenges, such as methodological issues including legal and ethical issues, and clinical integration and utility issues, must be overcome to realize the promise of AI and ML in orthodontics, having in mind that the progress is often like two sides of the same coin, with advantages and disadvantages, and among these latter the fact that AI may prompt DIY orthodontics by patients. In fact, digital technology is not without its dangers and negatives.

The increased availability of 3D printers and digital tools has also allowed the emergence of the DIY, raising the prospect of orthodontist-less diagnosis and therapy in the future. There have been several new reports of patients attempting their own orthodontic treatment with homemade appliances. Additionally, some companies are now providing direct delivery aligners without the patient needing to be properly assessed and diagnosed by orthodontists with the obvious risks involved.[27] Thus, AI and ML should be governed by orthodontists, not the opposite, as we cannot allow, for the sake of our patients, that our clinical practice is controlled by AI.

So, what is to become of orthodontics in this time of AI? Our fate is going to change. The practice of orthodontics will never disappear, but our role as clinicians hinges on what we do next.[28] How should we prepare for these coming times? The most obvious step is to adapt clinical education to the digital world.

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