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Radiomics and Machine Learning in Oral Healthcare

André Ferreira Leite, Karla de Faria Vasconcelos, Holger Willems, and Reinhilde Jacobs**

The increasing storage of information, data, and forms of knowledge has led to the development of new technologies that can help to accomplish complex tasks in different areas, such as in dentistry. In this context, the role of computational methods, such as radiomics and Artificial Intelligence (AI) applications, has been progressing remarkably for dentomaxillofacial radiology (DMFR). These tools bring new perspectives for diagnosis, classification, and prediction of oral diseases, treatment planning, and for the evaluation and prediction of outcomes, minimizing the possibilities of human errors. A comprehensive review of the state-of-the-art of using radiomics and machine learning (ML) for imaging in oral healthcare is presented in this paper. Although the number of published studies is still relatively low, the preliminary results are very promising and in a near future, an augmented dentomaxillofacial radiology (ADMFR) will combine the use of radiomics-based and AI-based analyses with the radiologist's evaluation. In addition to the opportunities and possibilities, some challenges and limitations have also been discussed for further investigations.

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1. Introduction

Technology is advancing rapidly, sometimes even surpassing scientific advancements and validation. Nowadays new tools may allow to integrate multiunit inputs leading to a more efficient approach to enable solving complex problems.[1] This is surely true in oral healthcare, where the increasing storage of information, data, and forms of knowledge have led to the development of new technologies and methods of human interactions with machines. In this context, artificial intelligence (AI), machine learning (ML), and deep learning (DL) have actually become commonly used terms in several areas of modern daily life, such as in medicine and dentistry.[2–4]

ML and its subclass DL are techniques that enable computer systems to improve with experience and data. Where ML uses hand-designed features, DL achieves even greater power by learning its features.[5] Radiomics relates to both, as it is the study that aims to extract quantitative features from medical images for improved decision support.[6] Thus, these radiomic features can serve ML applications.

A comprehensive review of the state-of-the-art of using radiomics and ML for imaging in oral healthcare is presented in this paper. Initially, the concepts of AI, ML, and DL are described. Second, an overview of how these techniques have permeated the health sciences is given. Finally, the article highlights the promising applications provided by radiomics and DL in dentomaxillofacial radiology (DMFR). In addition, opportunities, challenges, and limitations of these techniques are also discussed for oral healthcare application.

2. Concepts of AI, ML, and DL

Intelligence is defined as the ability to acquire and apply knowledge and skills. Artificial is an adjective referring to the fact that it does not appear in nature. AI could hence be described as the non-biological ability to accomplish complex tasks.[7] Examples of AI applications include image processing, chess-playing systems, and processing of formal languages. More specifically, it is able to recognize patterns in an imaging exam to detect a disease. AI has a hierarchical relationship with ML and DL, as shown in **Figure 1**.

ML is a technique that enables computer systems to learn patterns from large datasets, opposed to AI where knowledge can also be explicitly programmed into the algorithm.[5–7] If ML

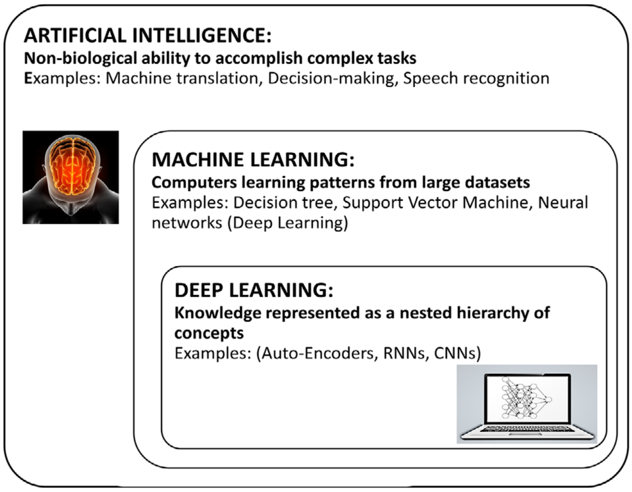

Figure 1. Diagram showing how DL is a kind of ML, which is in turn a kind of AI. Each section of this diagram contains the concept description and some examples of AI technology.

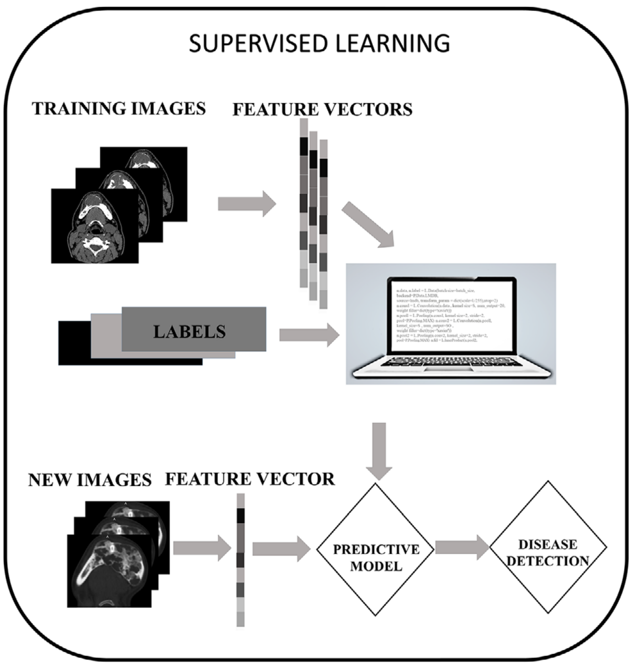

Figure 2. Example of a supervised ML network that uses DL. The network uses labeled images for training a predictive model. This model can be used for, e.g., diagnostics.

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algorithms are developed to train on a labeled dataset, they are called supervised. These algorithms can be trained for predictive tasks (**Figure 2**). The process to detect structures in data without labels is called unsupervised learning.[8–10] Therefore, ML require hand-engineered feature extraction from inputs.

Although DL is a subset of ML, it is an increasing powerful approach to AI. Traditional ML depends on carefully designed engineered features, requiring human expertise and complicated task-specific optimization. However, DL methods learn the features directly from data. DL allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. Therefore, DL methods have the ability to learn complex data representation, being more robust against human (inter-reader) variability. In this way, DL bypasses traditional ML methods. On the other hand, it requires a larger amount of data and higher computing power. It is used in research domains such as computer vision, speech analysis, and natural language processing.[11] DL represents its knowledge as a nested hierarchy of concepts, with each concept defined by simpler concepts.[5,12,13]

The underlying structures of DL are artificial neural networks. These are layers of a simple processing units, called neurons, sequentially stacked one after the other via weighted connections.

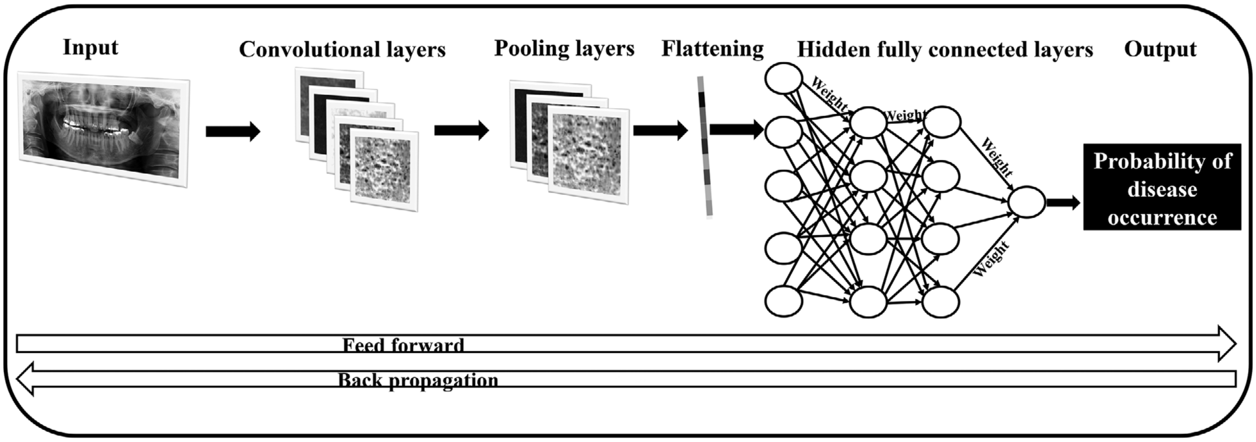

Figure 3. Example of a CNN used to predict dental disease based on information extracted from a panoramic radiograph.

Several types of deep neural networks exist. In practice, both recurrent neural networks (RNNs) and convolutional neural networks (CNN) are used.[5,14] RNNs deal with sequential input data, including speech and language. CNNs are specialized to deal with data with a grid-like topology, such as 2D and 3D images.[15]

While imitating neural connectivity patterns in the human visual cortex, the basic architecture of a CNN consists of a one or more convolutional layer, a pooling layer, and a fully connected layer.[16] The moment that training data enter the input layer, the learning process begins. The data are then sequentially passed to neurons in the next layer until the output is reached. This process is called forward propagation. This generated output is then compared with the ground truth and their difference is computed. These errors are back-propagated through the neural network, and the weights of the connections between the neurons are updated to minimize this error. After the training phase, including multiple iterations of forward and back propagation, the performance of the CNN is assessed by an unseen test data set.[5,17] This process is illustrated in **Figure 3**.

Although the artificial neural networks were introduced in the 1940s,[5] initially these were extremely limited in its ability to solve problems, mainly due to the overfitting problems with training of deep architecture, lack of computing power, and primarily the insufficient data to train the computer system.[16] Recent substantial advances in computing power, improved data storage facilities, and new DL algorithms allow computers to perform an increasing number of tasks that have historically not been possible.[18] Nowadays, there are multiple DL frameworks available, the most promising being Tensorflow, PyTorch, Sonnet, Keras, and MXNet.[19] Among the various current applications of AI, there is an increase in the use of AI tools in the health area, where CNN takes up an important role in the processing of medical images.

3. DL Applications in Healthcare

Digital and biological revolutions in genomics, imaging, and other health domains have been modifying healthcare practices. The current concept of personalized or precision healthcare takes into account these advances in DNA sequencing, physiological, and environmental monitoring, advanced imaging, and behavioral tracking. Consequently, these transformations may improve risk assessment, diagnostic, and prognostic capabilities for several diseases. In this context, AI tools may help to extract more and better information from the patient in order to achieve accurate outcomes at lower health costs.[20–22]

With the increasing availability of digital medical information in the form of electronic health records, and the fast development of big data analytic methods, AI might assist health professionals with difficult decisions in complex clinical situations.[9,23] In this way, the worldwide interest in AI applications is high and growing rapidly.

The improvement of CNNs strengthens its use in healthcare. A previous study has demonstrated that a trained CNN was able to differentiate abnormal from normal electroencephalographies (EEGs). In this study, 7.671 EEGs were used for training the neural network, and 851 were used for its testing. The reference test was established by two experts in EEG. Regarding the performance, the area under the curve was 0.924 for the developed model.[24]

Recent studies have demonstrated that CNNs may increase diagnostic accuracy or prediction of various diseases, such as cardiovascular diseases,[25,26] metabolic bone diseases,[27,28] neurological diseases,[29,30] ophthalmological diseases,[31] infectious *NTHL1* diseases,[32,33] as well as several benign and malignant tumors.[34–36] One of the most promising applications of CNNs is analyzing radiological images. As radiomics investigates the extraction of features from radiological images, CNN can support and co-develop these techniques. A recent paper even demonstrates CNN outperforming radiomic analysis for multiparametric breast magnetic resonance imaging (MRI).[37] Interaction of DL CNN and radiomics is the topic of next section.

4. Radiomics and DL Applications in Radiology

Advances in diagnostic imaging modalities have increased in terms of complexity and volume of generated digital data. These factors led to the creation of a new approach to imaging diagnosis called radiomics.[38] It consists of algorithms that

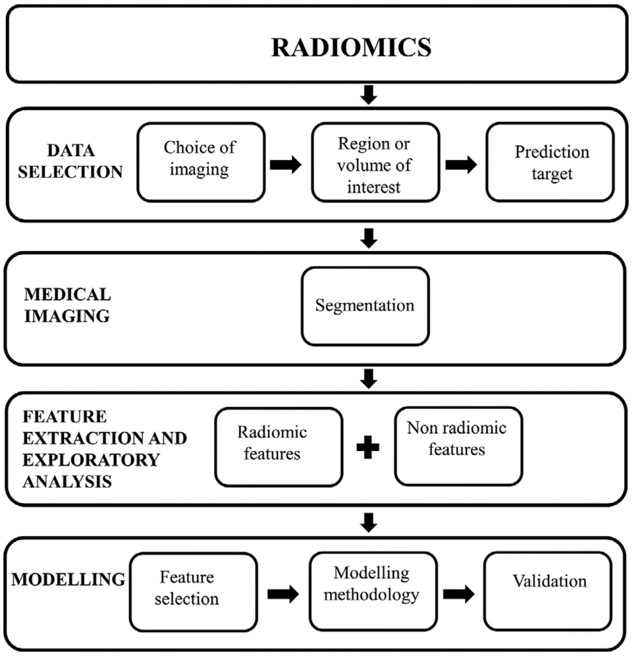

Figure 4. The workflow for a radiomics analysis.

decompose input images into basic features that may be used to classify or interpret the image, such as edges, gradients, shape, signal intensity, wavelength, and textures. Thus, radiomic analysis may be simply defined as an extraction of quantitative features or parameters, measurable and mineable from radiological images. Therefore, hundreds of abstract mathematical features, generally not extractable by the human eye, can be defined or detected on imaging modalities by using software.[5,7,21,39] **Figure 4** demonstrates the necessary steps in a radiomics study.

The association of Radiomics-based data with biological and clinical endpoints may help clinical decision-making, improving diagnostic, prognostic, and predictive accuracy.[40] A previous study with 102 patients analyzed whether radiomics features from fluorodeoxyglucose positron emission tomography/computed tomography (PET/CT) and MRI could contribute to prognoses in histologically proven locally advanced cervical cancer. For this purpose, 69 patients were used for training and 33 for testing. Radiomics features extracted from both imaging modalities, such as intensity, shape, and texture have demonstrated higher accuracy for predicting recurrence (94%) and lack of loco-regional control (100%) than only clinical parameters (50–60%).[41]

In this context, radiology has been moving from a subjective perceptual skill to an objective science.[4] Some authors have considered that radiomic features may represent a kind of "mathematical imaging phenotype" of disease expression. Therefore, they represent the bridge between medical imaging and personalized medicine.[39]

In the search for personalized medical practice, AI applications, especially DL, may also play an important role. They have a potential to perform high-throughput processing of radiological images in correlating the images (and radiomics data) to other data on genomics, proteomics, clinical information, or response to therapy. Therefore, DL holds promise to improve both quality and quantity of future image processing, and may help radiologists to analyze images that contain vast data information.[15,42]

Consequently, automatic methods based on deep neural networks have been tested for several purposes, which are as follows: classification, image registration, segmentation, lesion detection, image retrieval, image guided therapy, image generation, and enhancement.[5,6,38,43–46] Most recently, radiomics and AI research have been advancing in the dental field, revealing the potential of these technologies to substantially improve clinical care.[47–69]

5. AI Revolutionizing Oral Health Care

As the use of AI in the entire medical field increases, the role of AI in dentistry has been progressing remarkably.[3] Generally speaking, the use of AI tools in dental practice brings new perspectives for the diagnosis, classification, and prediction of oral diseases, for treatment planning, and for the evaluation and prediction of outcomes. CNN may help the dentist in the daily life, minimizing the possibilities of human errors. Furthermore, the teaching of dentistry should also be modified in order to incorporate all these technologies in undergraduate and postgraduate courses. **Table 1** presents possible applications of AI in several areas of dentistry, based on recent articles.

Although the use of AI tools has been growing in dentistry, the number of published articles is significantly smaller than of the other medical areas, especially radiology. An advanced search in Pubmed database on November 27, 2019 for the term "artificial intelligence" listed 95 413 publications; and when combined with the word "Radiology," 6474 articles were found. On the other hand, 659 articles were listed when the term AI was combined with dentistry. Concerning AI in dentistry, the most promising area for applying this technology is DMFR.[3] Table 1 depicts that many previous AI research in different dental specialties were imaging-based studies. When combining the term "artificial intelligence" and "radiology" and "dental" or "oral," 196 articles were retrieved in Pubmed database. Some recent studies have demonstrated that CNN-based methods may be used in dental images for several purposes, as demonstrated in Table 2.[50,52,53,57,60–62,64,66,69–85]

A recent scoping review has discussed the applications of deep CNN for dental image diagnostics. Thirty-six studies were included in this review. A great variability could be observed regarding the studies, tasks, and used performance metrics. The most frequent tasks were tooth classification and detection of carious lesions, with accuracy varying from 0.77 to 0.98 for the former task, and 0.82 to 0.89 for the second task.[86]

Few heterogeneous studies have investigated the promising capacity of AI tools for automatically segmenting head and neck structures.[69–71] The aforementioned studies have used different image modalities as panoramic, CBCT and CT, to segment tooth and jaw bones. All of them have achieved good results. However, the training and testing datasets were small. The possibility of automatically segmenting head and neck structures may save time for the radiologist's practice and minimize errors. Manual segmentation is a time consuming and operator depending task. Advances in the automated method may improve

Table 1. Recent studies that discussed the possibilities and perspectives for applying AI tools in different fields of Dentistry.

DENTISTRY FIELD	APPLICATIONS
Periodontics	Classification and control of dental plaque;[47] segmentation of gingival diseases;[48] automated evaluation of periodontal pockets;[49] diagnosis and prediction of periodontally compromised teeth[50] **imaging study**; detection of malodor.[51]
Orthodontics	Automated identification of cephalometric landmarks[52] **imaging study**; prediction of growth and mandibular morphology in class I, II and III patients[53] **imaging study**; analysis of biological markers for orthodontic tooth movement;[54] understanding of aetiopathogenesis of craniofacial diseases;[54] automated identification of craniofacial syndromes;[54] prediction of treatment and outcomes models;[54] genetic risk assessment of orofacial cleft;[55] identification of epigenetic changes in the normal and abnormal craniofacial development;[54] analysis of mandibular condyles and temporomandibular joint disorder[56] **imaging study.**
Restorative dentistry	Evaluation of lifespan of dental restorations;[3] improving accuracy of caries diagnosis[57] **imaging study.**
Endodontics	Location of minor apical foramen in cadavers;[58] characterization of gene expression of radicular cyst and periapical granuloma;[59] detection of vertical root fractures in intact and endodontically treated teeth[60] **imaging study**; evaluation of periapical lesions (bone repair) after treatment[61] **imaging study**; assessment of root morphology on radiographs[62] **imaging study.**
Forensic application	Automated determination of skeletal and dental ages[63,64] **imaging studies**; autopsy with AI-driven robotics methods[65]
Craniomaxillofacial Surgery	Differentiation of different jaw tumors[66] **imaging study**; prediction of the occurrence of bisphosphonate-related osteonecrosis of the jaws associated with dental extraction[17] **imaging study**; assessment of the impact of orthognathic treatment on facial attractiveness and estimated age;[67] autonomous AI-driven robotics for performing surgeries and biopsies.[65,68]

AI, artificial intelligence.

virtual surgery planning, radiation therapy planning, and radiomic analysis.[5,18]

Another positive application of CNN consists of the possibility of optimizing the images, generating images of better quality, with low radiation dose and with little production of scattering or artifacts.[87] Such AI optimization algorithms seem promising and could be applied on different imaging modalities, especially for correcting technical positioning errors on panoramic radiographs or for enhancing quality on computed tomographic images.[72–74] Toward the future, larger studies should be carried out to verifying the proposed optimization, which can be surely helpful to reduce radiation dose, scattering, and artifacts.

The combination of radiomic and AI tools in dentistry are still limited to the evaluation of osteoporosis status on dental panoramic radiographs.[75,76] Some authors have evaluated the diagnostic performance of three deep CNN-based computer-assisted systems for detecting osteoporosis on 1268 dental panoramic radiographs. In this study, the grey level of a region of interest was the input to the networks. Experienced oral and maxillofacial radiologists were considered as the reference test. For the training and validation phases of the study, 1068 radiographs were used. For the testing phase, 200 radiographs were selected. Regarding the performance, the areas under the curve values obtained were 0.976, 0.999, and 0.998 for the three different neural networks.[75]

Several radiomic features may be extracted from 2D or 3D images, based on size and shape; descriptors of the relationship between image pixels or voxels, gray-level occurrence matrix, run-length matrix; descriptors of histograms of image intensity; textures extracted from filtered images; and complex fractal features, among others. These imaging features may aid in the early detection of malignant or many bone diseases. They can also be used to predict treatment response to therapies, including oncotherapy, and to estimate functional parameters.[18–37,39–41] The combination of these imaging features with other clinical and genetic data may improve the capacity of detecting and predicting diagnosis and outcomes. Integrated data processing in oral healthcare may allow rendering more patient-specific diagnosis and personalized treatment planning.[20]

The most investigated applications of DL algorithms in DMFR were for the detection, classification, or diagnosis of diseases or anatomical structures, such as classification of teeth and mandibular morphology; differentiation of jaw tumors; and detection of root fractures, Sjögren's syndrome, maxillary sinusitis, calcified carotid atheroma's, caries, and periodontal diseases.[50,52,53,57,60–62,64,66,77–85] However, the studies were heterogeneous and mainly based on 2D images (intraoral or extraoral radiographs). Therefore, several possibilities still exist concerning the use of AI tools in DMFR. On the other hand, some challenges and limitations need to be addressed to optimize radiomic and ML techniques for dental care.[88] Opportunities and challenges for DMFR are addressed in the last two sections.

6. Augmented DMFR: A New Perspective

As in medical radiology, the possibilities and perspectives of the use of radiomics-based and AI-based analyses combined with the radiologist's analysis will revolutionize the DMFR,[89] as shown in **Figure 5**.

Augmented DMFR (ADMFR) will be a powerful auxiliary tool for achieving the precise and personalized oral healthcare. This new approach will improve diagnostic capabilities, with better accuracy and predictive models for several oral diseases. DL may correlate radiomic features with other clinical and genetic data. New imaging biomarkers will be defined. The predictive power of the imaging modalities will be expanded including outcome factors and prognosis associated with each kind of selected treatment. Automated segmentation of dental and craniofacial structures will also improve the evaluation of tissue and organs, disease extent, and burden.[90,91]

Concerning image acquisition, new protocols may be used or created, as AI tools may optimize images, reducing the radiation dose, and correcting scatter and artifacts. The AI-driven management and mining of large imaging databases may also impact

Table 2. Brief summary of the most recent and relevant studies concerning AI applied in DMFR.

Application	[Reference] Year	Imaging modality	Method	Aim	Remarks on dataset size	Main conclusions
Image segmentation	[69] 2018	Panoramic radiographs	CNN and 2D coupled shape model	To test a novel method for automatic teeth segmentation	Small (14 images)	New method performed better than state-of-the-art methods.
	[70] 2019	CBCT	CNN and RNN	To develop a fully-automated image analysis for mandible and anatomical landmark segmentation	Small (50 images with high variability)	New method showed superior efficacy compared to state-of-the art methods.
	[71] 2018	CT	CNN	To develop an automated method of mandible segmentation	Small (10 images)	New method was promising and accurate.
Image optimization	[72] 2018	Panoramic radiographs	CNN	To estimate and correct positioning errors of patients' dental arch	large (5166 images)	CNN-based auto-positioning method for dental arch was effective in providing reconstructed panoramic images of stable diagnostic quality
	[73] 2018	CT	CNN	To develop a neural network for CT image super-resolution	Moderate (52 images)	CNN method yielded high-resolution images based on low-resolution images
	[74] 2019	CBCT and micro-CT images	CNN	To develop neural networks for resolution enhancement	Large (5680 cross-sectional slices of 13 teeth + test et of 1824 slices of 4 teeth)	New method showed better result than state-of-the-art reconstruction-based super-resolution approaches in terms of both quality metrics and image-segmentation-based-analysis.
Radiomics	[75] 2018	Panoramic radiographs	CNN	To evaluate the performance of a CNN for detecting osteoporosis	Large (1069 images for training and validation; 200 images in test database)	CNN showed high agreement with experienced oral and maxillofacial radiologists in detecting osteoporosis.
	[76] 2018	Panoramic radiographs	CNN	To develop a deep Octuplet Siamese Network (OSN) to learn and fuse discriminative features for osteoporosis condition prediction	Large (55 000 images in 286 texture categories used for training dataset; 56 images without and 52 images with osteoporosis as test database)	New method outperformed all other state-of-the-art methods in osteoporosis categorization.
Detection, classification or diagnosis	[62] 2018	Panoramic radiographs	CNN	To evaluate the performance of a DL system for classification of the root morphology of mandibular first molars	Large (760 images from 400 patients)	DL system showed high accuracy in differential diagnosis of single or extra root in first molars.
	[77] 2018	Dental periapical radiographs	CNN	To develop a neural network for recognizing and classifying teeth position	Small dataset (32 teeth)	The method was effective in recognizing and classifying the 32 teeth position
	[78] 2019	Panoramic radiographs	CNN	To develop a neural network for detecting and numbering teeth	Large (1352 with test set comprised of 222 images)	The performance of the proposed computer-aided diagnosis solution was comparable to the level of experts.
	[66] 2018	Panoramic radiographs	CNN	To differentiate jaw tumors (ameloblastoma and keratocystic odontogenic tumor)	Large (training on 400 images and the test set of 100 images)	Sensitivity, specificity, accuracy, and diagnostic time using CNN were comparable to that of manual diagnosis by oral maxillofacial specialists.

(*Continued*)

Table 2. Continued.

Application	[Reference] Year	Imaging modality	Method	Aim	Remarks on dataset size	Main conclusions
	[61] 2018	Dental periapical radiographs	CNN	To classify dental treatment qualities of periapical lesions	Large (196 images)	Automated approach to classify dental treatment yielded good accuracy results that was comparable to expert-level dentists.
	[52] 2017	Lateral cephalometric radiographs	CNN	To develop an end-to-end DL system for cephalometric landmark detection	Large (300 images)	Automated approach to identify anatomical landmarks was successful and comparable to dental experts.
	[64] 2017	CBCT	CNN	To develop an automated method for classifying tooth types	Moderate (52 images)	By increasing the number of training samples by rotation and intensity transformation (data augmentation), a high accuracy of 91.0% was achieved.
	[79] 2017	Contrast-enhanced CT	CNN	To evaluate the accuracy of DL image classification for diagnosis of lymph node metastasis	Moderate (45 cases with 127 histologically proven positive cervical lymph nodes and 314 histologically proven negative lymph nodes)	CNN yielded diagnostic accuracy similar to those of the radiologists.
	[80] 2018	Contrast-enhanced CT	CNN	To develop a neural network for detecting head and neck cancer nodal metastasis and extra nodal extension	Large (training dataset comprised of 2875 CT-segmented lymph nodes. The test dataset of 131 images)	The model could accurately predict extra nodal extension and nodal metastasis
	[81] 2019	Panoramic radiographs	CNN	To apply DL methodology to detect calcified carotid atheroma	Moderate (65 images for training data)	Atheromas were detected with a sensitivity of 75%, a specificity of 80%, and an accuracy of 83%.
	[82] 2018	Panoramic radiographs	CNN	To differentiate normal sinus from inflamed, and to verify the accuracy of the method for diagnosing maxillary sinusitis.	Large (Training data consisting of 400 images with healthy sinuses and 400 with inflamed sinuses. Testing dataset with 60 healthy and 60 inflamed sinuses images)	The diagnostic performance of the DL system for maxillary sinusitis was comparable to dental experts and higher than dental residents.
	[60] 2017	Dental periapical radiographs and CBCT	CNN	To design a neural network and test its efficacy to diagnose vertical root fractures inintact and endodontically treated teeth.	Large (Training data comprised 240 images)	The designed neural network could be used as a proper model for the diagnosis of vertical fractures, especially on CBCT images.
	[83] 2017	Dental periapical radiographs (*ex vivo* teeth)	CNN	To develop an artificial neural network for vertical root fracture detection	Large (200 images for training and testing)	The CNN demonstrated high accuracy measurements for being used as a model for vertical root fracture detection
	[85] 2019	CT	CNN	To estimate the performance of a DL system for detection of Sjögren's syndrome	Large (400 images for training and 100 for testing)	The performance of the DL system was comparable to the experienced radiologists, but the unexperienced radiologists showed lower accuracy to detect the disease.

(*Continued*)

Table 2. Continued.

Application	[Reference] Year	Imaging modality	Method	Aim	Remarks on dataset size	Main conclusions
	[57] 2018	Dental periapical radiographs	CNN	To evaluate the efficacy of CNN algorithms for detection and diagnosis of dental caries	Large (2400 images for training, 600 images for testing)	The diagnostic accuracies of premolar, molar, and both premolar and molar models were 89.0% (80.4–93.3), 88.0% (79.2–93.1), and 82.0% (75.5–87.1), respectively.
	[50] 2018	Dental periapical radiographs	CNN	To develop a CNN system and to evaluate the usefulness and accuracy for diagnosis and prediction of periodontally compromised teeth	Large (1392 images for training; 348 images for testing)	The method was as effective as experienced periodontists for positively diagnosing and predicting periodontally compromised teeth.
	[84] 2017	Lateral cephalometric radiographs	CNN	To develop an AI decision-making model for the diagnosis of extractions for orthodontic purpose, and also to evaluate the validity and accuracy of this model.	Moderate §96 images for training and 60 for testing)	The success rates of the classifiers were 93% for the diagnosis of extraction vs nonextraction and 84% for the detailed diagnosis of the extraction patterns in total.
	[53] 2017	Lateral cephalometric radiographs	CNN and Support Vector Machine	To predict the mandibular morphology through craniomaxillary variables in patients with skeletal class I, II and III	Training data comprised 229 images	CNN showed a high predictability ability of the mandibular morphology in the three skeletal classifications.

AI, artificial intelligence; CBCT, cone beam computed tomography; CNN, convolutional neural network; CT, computed tomography; DL, deep learning; RNN, recurrent neural network.

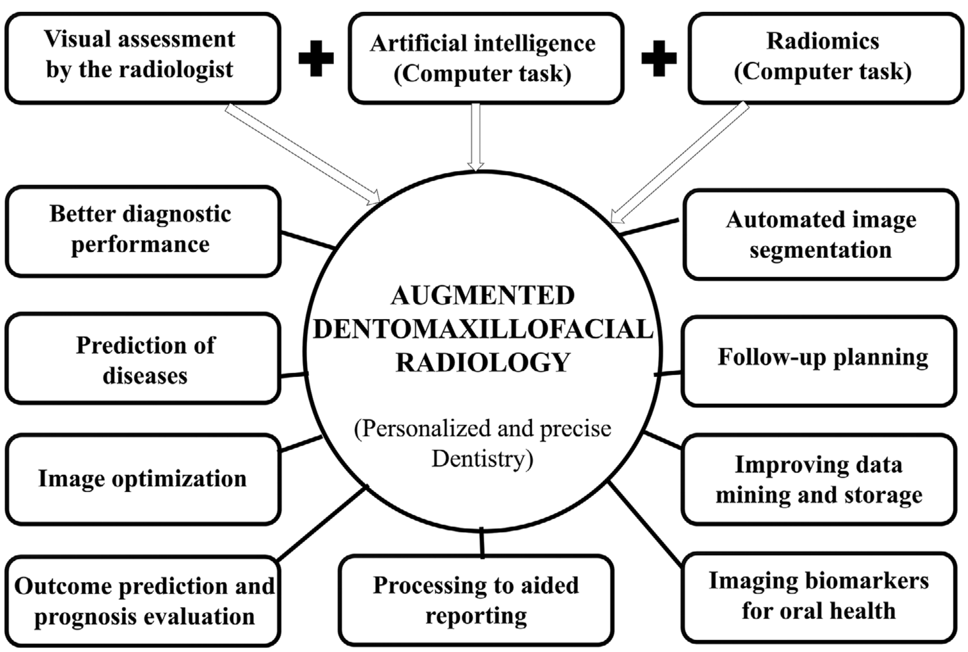

Figure 5. ADMFR: new perspectives and possibilities when combining radiologist's analyses with AI and radiomics tools.

the daily workflow by pre-analyzing and prioritizing cases. This technique can also facilitate the radiologist's reports, enabling the association of words, images, quantitative parameters, and minimizing errors. Therefore, ADMFR will add value improving diagnosis, surgery, and treatment planning, predicting diseases and outcomes, and consequently creating an accurate robust clinical decision support process. Furthermore, radiologists may experience a more efficient workflow with automated suggestions for complex case processing and prediction of surgical complications.

As these DL algorithms have been modifying radiology practice, the process of learning in radiology will be similarly affected.[92] The way that our students and faculty members access and interact with information and with the physical world will continue to change and evolve. Students and practitioners will inhabit a future in which AI and virtual reality might steer personalized educational experiences.[93]

Many e-learning tools have increasingly been used in dental curricula to support traditional teaching, such as computer-assisted learning, web-based learning, and mobile-enhanced learning. However, the number of studies that have used e-learning methods in DMFR is still scarce.[94] In fact, this use of technology is particularly relevant in radiology, where visual information, central to its practice, and also the complexity and the large volume of data, can be presented and reinforced in innovative ways.

More recently, some adaptive learning platforms (ALPs) have been developed for medical education.[95,96] Based on DL algorithms, these platforms are able to analyze students' performance in real time and suggest specific content (videos, games, texts, etc.) for the needs of each one. Behind this virtual learning environment, with contents grouped and delivered in a variety of ways, there is an algorithm capable of suggesting a student the way he tends to learn better. Therefore, these platforms may help teachers, managers, and educational networks to give more autonomy to students and to customize the learning process.[97]

7. Challenges and Limitations of ADMFR

Although the results of previous AI research have been extremely promising, the studies are still preliminary. Some general and intrinsic challenges exist. In general, the mathematical processes underlying AI hinder the understanding of outcomes by radiologists, i.e., it is hard to explain, which affects their opinion about the use of these computer-aided techniques in daily practice. However, the radiologist's work is prone to subjectivity, variations across observers, and the adverse effect of fatigue. Hence, mathematical processes should not be considered as a threat for the DMFR specialty and dental practice. On the other hand, it is an opportunity for improvement, as radiomics and ML techniques might add value to the radiologist's current practice surely in case of integrated processing of multiple imaging and clinical features fitting a specific diagnostic task.[41]

Moreover, some intrinsic challenges exist to increase the usage of AI in DMFR, similar to medical imaging.[21] The main challenge is the availability of big data concerning dental images. Another challenge is to calculate a minimum sample size to perform a specific DL-task. In a recent scoping review, datasets varied between 10 and 5166 images (mean 1053 images). This heterogeneity is mainly related to different tasks and target accuracy.[86] For overcoming this limitation, many studies that used small sample sizes have used some strategies, such as data augmentation and transfer learning.

Data augmentation strategy is generally used for the training data to reduce the risk of overfitting. By generating different images from the original images, such as cropped images with different locations, noise-added images, mirrored images, among others, this technique aims to increase the size of the dataset.[15] Furthermore, transfer learning is also a widely applied technique on trained networks over smaller datasets. Knowledge gained by a pretrained network in one large dataset (generally using nonmedical images) is transferred to another dataset with a completely different kind of data (such as medical images). The pre-trained network may be used as a feature extractor, or by fine-tuning the last fully connected layers. They let the model learn some basic low level features of the image from a large dataset, but use the high level features to be more specific to the training data.[98]

DL studies often require a large amount of data because the features are learned directly from the data via an end-to-end process.[92] Furthermore, during training for diagnostic AI, datasets should also be carefully composed and adequately labeled by experts to render the prediction robust and accurate.[21] Further studies should be conducted on large datasets in order to verify whether CNNs could assist in detection and prediction of early-stage of dental and osseous changes that are almost invisible to the human eye, and process the data quickly and accurately.

One should also realize that high variability of imaging protocols may impede comparisons among different studies, and the development of multi-institutional large databases. Another intrinsic challenge is related to the establishment of the ground truth (gold standard) for validating classifications or predictive models resulted from AI studies.[21] As this ground truth serves for training and validating the quality of the AI, it should be carefully considered by experts and this might require validation itself. A further issue that might need to advance in the future is the computational speed; which needs to be clinically realistic to enable its use in clinical practice.

To overcome these challenges and limitations, it is encouraged that radiologists and AI experts work together, as such to result in robust and clinically applicable use of radiomics and AI in Dentistry.

8. Conclusions

DL, the most promising and active field of AI, improves with a steady pace. This technique is exceptionally versatile to perform tasks as it improves with experience and data. Therefore, opportunities arise in the whole medical field. Research in dentistry remains preliminary, but shows great promise.

AI and radiomics could support specialists in decision-making, by extracting in a consistent way the most relevant features from vast amounts of data. Another use case for DL is to make recommendations to specialists, to both improve the accuracy of a correct diagnosis and treatment, and its speed. AI could improve each single stage of dental practice and hence its outcomes. This would unlock personalized Dentistry, enabling the best possible outcome for each individual.

To reach this goal, more interdisciplinary research is needed to develop AI tools that are explainable and robust. Once these challenges are addressed, human–machine interaction could become mainstream in dental practice, challenging on its turn the way we should educate the current generation of students.

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Conflict of Interest

The authors declare no conflict of interest.

Keywords

CBCT, machine learning, oral health, radiomics

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