ARTIFICIAL INTELLIGENCE IN DENTAL RADIOLOGY

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Abstract

Artificial intelligence (AI) had a renaissance in late 1990s when the expert system of IBM (Deep Blue), defeated global chess champion Garry Kasparov. Early in the twenty-first century, the world was startled by the capabilities of powerful AI, such as Alphago and Watson, which exceeded human capabilities in domains which have been exclusive to humans. Deep learning (DL) has just made it possible for autonomous cars to operate on public roads and pass the Turing test, specifying that they are intelligent. AI is being utilized more frequently in healthcare for automating processes, especially in diagnosis to help physicians making decisions. Research and studies indicate that, in the opinion of experts, AI applications might be more beneficial for non-specialists and novices.

Key words: Artificial intelligence, Dentistry, Dental Radiology

Introduction

Though previously thought to be a far-off, fantastical dream for distant future, AI is slowly starting to become a reality in a variety of industries, such as the medical and dental fields. In dentistry, AI has recently been used for analyzing radiographic images, specifically in oral and maxillofacial (OMF) radiography.
John McCarthy used the term AI in the year 1989 for describing machines which mimicked human knowledge and behavior. Through the advancement of hardware, such ability was increased by orders of magnitude. "Can synthetic intelligence update the function of clinician inside the analysis of diseases?" is the question that physicians ask most often.
Artificial intelligence AI had a renaissance in late 1990s when the expert system of IBM, Deep Blue, defeated global chess champion Garry Kasparov. Effective AI, like Alphago and Watson, have taken the world by storm in early twenty-first century because they have long since surpassed human capabilities in domains that have been exclusive to humans. DL has lately made it possible for autonomous cars to operate on public roads as well as pass the Turing test, suggesting that they are intelligent (Wang et al., 2016). AI is gradually permeating each part of our life through a variety of services like speakers powered by AI, content recommendation systems, and more. The emergence of DL presents appealing perspectives for the mechanization regarding image analysis in medicine and dentistry. Significant progress was achieved in every field of AI, including medical fields like robotic systems, data mining, medical image analysis, and natural language processing (Wang et al., 2016).

Literature review

1. Artificial Intelligence AI

AI is widely used in healthcare and dentistry. Due to the advent of various software programs installed on many medical equipment, traditional dentistry has been increasingly replaced by digital dentistry recently (Crevier, 1993). As more and more individuals attempt to utilize technology for making a diagnosis which allows them to work more accurately and faster, reducing expenses and the amount of the medical errors, AI in public healthcare has gained traction. The pursuit of advancement and innovation in order to provide high-quality healthcare will be the foundation of the future. This subject has sparked a lot of interest in technological science publications, particularly those that

discuss the application of AI to different medical specialties. Alan Turing has been the first to question if machines could think in the year 1950 (Wang et al., 2016).
Healthcare AI programs are growing, which is expected given the automation of jobs, particularly diagnostics to support physician decision-making. When AI is utilized for processing the vast amounts of data generated by healthcare services, it can yield a number of promises and benefits, including the ability of providing more predictive health care, make it focused and customized; identify symptoms more efficiently and accurately; utilize analysis results (lab tests, images, and so on.) automatically; create custom protocols of treatment plans; and make it easier for care teams to coordinate. As a result, AI opens the door to a new era of extremely early diagnosis through looking for and identifying signs of a particular disease. Since radiology uses digitally recorded images which are simply translated into computer language, it is actually the field where AI is most useful (Najafabadi et al., 2015).

2. Machine learning ML and deep learning DL

Synthetic intelligence includes the subset of machine-gaining knowledge. ML, more precisely, is the scientific study of the computer models which enhance performance via experience and don't require explicit instructions. As a result, for creating a model to generate decisions or predictions, a ML algorithm needs sample data (Bishop, 2016). Large classes of unsupervised, supervised, and reinforcement-gaining knowledge are used for classifying ML. Supervised learning addresses errors in classification and regression through learning labels for every input. Professional radiologists are required to perform annotation or labeling for facilitating supervised learning of diagnostic images. Systems which learn unlabeled data on their own and handle problems like distribution and clustering estimates are referred to as unsupervised learning systems. Reinforcement gaining knowledge of algorithms study from poor- or high-quality feedback in changing environments and are applied in robotics, computer vision, and video games (Bishop, 2016). Deep learning DL has advanced rapidly since Le Cun et al. (1989) introduced a deep neural network (DNN) which used a backpropagation algorithm to learn from data. This has been made possible by using high-performance graphics processing units, the resolution of overfitting problem (Hinton, 2007), where the predictions correspond extremely closely to training set, and the growing availability of big data. Complex and large image analysis is one of the uses for convolutional neural networks (CNNs), a sort of DL architecture which has significantly advanced AI recently. Radiology makes substantial use of CNNs for detection, classification, and segmentation; Figure (1) presents a schematic depiction of DL training about caries segmentation in periapical radiographs. To solve the problems of classification in radiographic image processing, complex CNN models were developed that can-do tasks ranging from accurately detecting the type of malignancy to identifying the existence of a disease (Hwang et al., 2018). As shown in figure (2), Detection is used in radiographic image analysis for identifying lesions or certain anatomical structures. CNNs for detection tasks have multiple extra layers for region suggestions or regression functions, even though they are comparable to CNNs utilized for classification tasks (Kim et al., 2019). By using photo segmentation, a variety of modalities, such as CT, plain radiography, ultrasound images, and MR, could be used to split anatomical systems or lesions into parts (Ker et al., 2018).

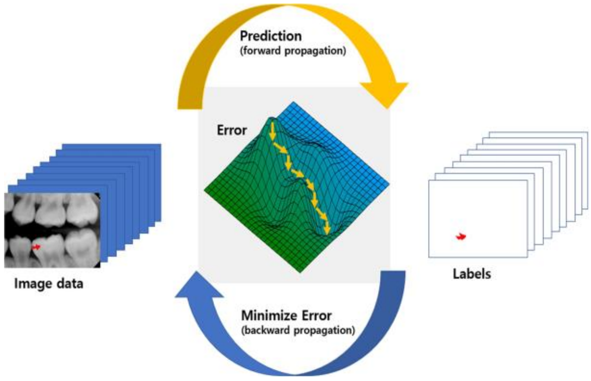

Figure (1): Schematic view of DL training with caries segmentation in the periapical X-ray. ***(Heo et al, 2021)***

A DL network learns from data as it advances through prediction and error reduction, lowering the error between its actual and predicted labels. This procedure, known as minibatches, is a progressive one that includes differentiating the error of partitioned datasets (Hesamian et al., 2019).

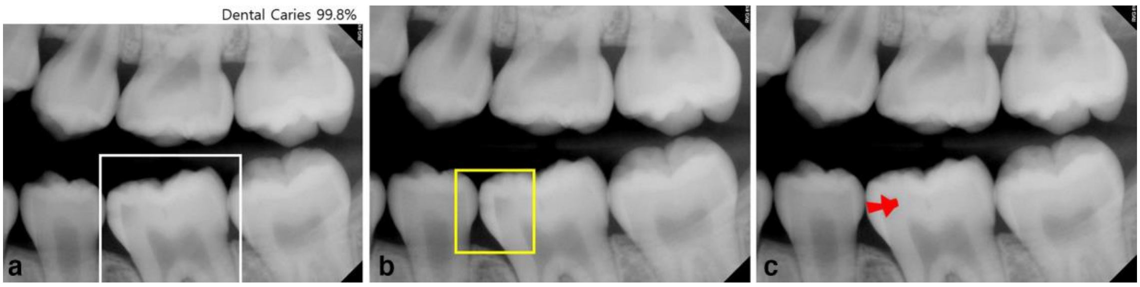

Figure (2) a. Dental caries is present in rectangular box on the image (i.e. the classification). b. Dental caries has been detected in the square box (i.e. the detection). c. A dental caries has been segmented on the image (i.e. the segmentation).

3. Data sets' preparation for the artificial intelligence

a. Data Collection and labeling:

Anonymizing the data, making sure it's standardized and representative, segmenting the region of interest, lowering noise, and annotating the data with reliable values are just a few of the crucial phases in the curation for radiography images (Hesamian et al., 2019). Ground truth in DL refers to expert-generated correct labels which are essential for increasing accuracy (Hesamian et al., 2019). There are two main approaches to labeling radiographic images: the first uses information from radiology reports, and it entails a radiologist analyzing the images and explaining them. The former approach can take a long time and lead to different labels being produced by various readers. Furthermore, because of overlapping features, 2D radiographs might make it difficult to identify and delineate 3D anatomical components (Figure 3). With the latter approach, you might need to confirm that the labels are accurate twice. In the end, the task at hand determines which approach is best. It's important to remember that in order to collect enough information, radiologists could need to have more than one person label the images. But radiologists' standards could differ throughout the process, thus coming to a consensus on labeling is essential to guaranteeing a trustworthy ground truth. Verifying agreement among radiologists can be done practically by using intra/inter-class coefficient (Costa et al., 2018).

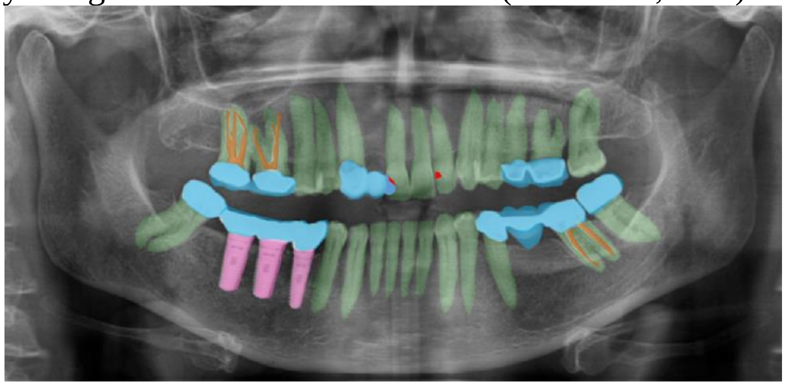

Figure3: Example of the complex labeling of the dental panoramic radiography. In 2-D radiographs where the structures overlap, it is usually difficult to clearly differentiate and outline 3-D anatomical structures. Green: teeth, sky: prosthodontics, pink: implant, red: dental caries, and brown: endodontic filling.

b. The acquisition of an extremely large dataset of high-quality

Producing high-quality labeled data is essential to improving deep learning DL applications' performance. But getting the data could be difficult and costly, particularly if there aren't enough case samples available. The application of data augmentation methods has grown in popularity as a solution to the problem. With such methods, the data set is altered in a variety of ways, whereas maintaining the same labels, including cropping, flipping, zooming, rotating, skewing, translating, elastic deformation, and altering the contrast or resolution (Figure 4). The data set could be efficiently increased through using this method to create additional data representations. The fourth figure (Do et al., 2020). Furthermore, problems with detection, classification, and segmentation pertaining to data scarcity were effectively resolved through the use of generation adversarial network -GAN-based artificial data augmentation approaches (Roth, *etal*., 2016).

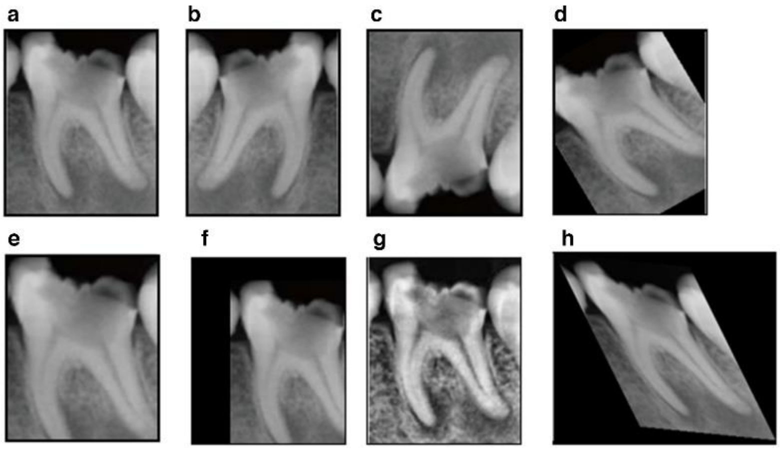

Figure4 Data augmentation example of the periapical X-ray. a. original image, b, c. Flip, d. Rotation, e. Zoom. f, Translation, g. Contrast adjustment, h. Elastic deformation. It should be noted that the apical lesion is removed in d, e, and f, which can lead to degrading performance of the periapical lesion detection model. ***(Heo et al, 2021)***

4. Artificial Intelligence in Oral and Maxillofacial radiology

Finding out regarding the AI research being done in oral and maxillofacial (OMF) radiology is important. Hwang et al. (2019) did a review and found that multiple studies in the dental sector were undertaken on the topic utilizing sources including PubMed, IEEE Xplore, and Scopus. Of the twenty-five articles they found, a total of two with dental tissues, twelve dealt with teeth, and two with osteoporosis. CNN was utilized as the main network component, according to the researchers. Additionally, they noticed a steady rise in the quantity regarding training data sets as well as published papers in various dental specialties over time. AI has been the subject of numerous works in the field of dentistry, mostly focusing on tasks like segmenting and classifying maxillofacial tumors and cysts, recognizing cephalometric landmarks, and diagnosing osteoporosis. AI has also demonstrated efficacy in the detection of periapical illness and periodontitis. Yet, the particular algorithm that is employed could affect how well AI model's function. An overview related to the imaging techniques as well as dental applications that were examined in DL studies is given in Table 1. Nagi and colleagues (2020) investigated the efficacy and possible applications of intelligence systems in dentistry and maxillofacial radiology in a recent work. An outline of the fundamental ideas of AI, such as fuzzy logic, machine learning ML, deep learning DL, neural network NN training, and learning programs and algorithms, was given. They also talked about the potential applications of AI in the future in fields including imaging biobanks, hybrid intelligence, and radiomics.

Table1. Dental applications and imaging modalities of the Data Learning in the systemic reviews.

Author (year)	**Application**	**Imaging modalities**
Hwang et al. (2019)	Tooth related 12	Intraoral6
	Dental plaque 3	Panoramic6
	Gingiva or periodontium 2	Cephalometric1
N = 25	Osteoporosis 2	CBCT4
	Others 5	CT1
		Others7
Schwendick *etal*. (2019)	General dentistry 15	Intraoral11
	Cariology 5	Panoramic10
	Endodontics 2	Cephalometric2
	Periodontology 3	Panoramic and CBCT1
N = 36	Orthodontics 3	CBCT5
	Dental radiology 2	CT1
	Forensic dentistry 2	Others6
	General medicine 4	
Hung *etal*. (2020)	Cephalometric landmarks 19	Periapical6
	Diagnosis of osteoporosis 9	Intraoral and panoramic1
	Maxillofacial cyst and/or tumors 6	Panoramic14
	Alveolar bone resorption 3	Cephalometric10
N = 50	Periapical diseases 3	CBCT14
	Multiple dental diseases 2	Others 5
	Tooth Types 2	
	Ohers 6	

CBCT: cone-beam Computed tomography, N, No. of reviewed articles, CT, computed tomography.

5. Radiographic diagnosis:

Researches on the application of AI in diagnosing a range of conditions, including periodontal disease, dental caries, odontogenic cysts and tumors, osteosclerosis, and disorders impacting the temporomandibular joints or the maxillary sinus, have been done in OMF radiology. "ORAD" is the name given to White's early AI invention from the 1990s. Since then, ORAD II (orad.org/cgi-bin/ orad/index.pl) was developed, offering OMF disease differential diagnosis (as illustrated in Figure 5 of Nagi et al., 2020). The technology allows users to enter radiographic as well as clinical data about a patient and gets a list of potential diagnoses. An early step in the development regarding AI is demonstrated by such example of its application in diagnosis. An ANN system was examined in 1999 research by Park et al. (Park et al., 1999) to determine in the case when oral squamous cell carcinoma had spread to the cervical lymph nodes based on magnetic resonance images. The ANN system outperformed every single MR imaging criterion, according to researchers. The observer entered the imaging features of lymph node metastases into the system throughout the investigation (as shown in Figure 6).

Reliable readings from experienced OMF radiologists provide accurate data that is essential for investigating AI. The capabilities of the examiner, which could vary dependent on their degree of experience and training, could affect how accurately dental caries is diagnosed. Therefore, the accuracy of data annotations ultimately determines how effective the AI model is. Researchers studying AI-powered automatic readings need to work with sophisticated data, such readings from experienced OMF radiologists, in order to get accurate results (Figure 7). The industry of dental sciences are in continuous development and deferent aspects involving analyzing of radiographic image like teeth localization and segmentation or studies of bone age and quality were done with the AI technologies (Schwendicke et al., 2019). Two dimensional and three-dimensional images were made and greatly developed using the deep learning along with the convolution neural network technologies which were created by researchers and were very helpful in dental industries (Hwang et al., 2019). DL also used in cutting-edge technologies that identify and categorized teeth in advanced image modalities. The dentists made well informed clinical decisions and lessen the time required for that by production of automated computer-aided designs outputs (Chang *etal*., 2020; Miki *etal*., 2017). In 2017, Doi stated that both osteoporosis and osteopenia could be diagnosed with the help of panoramic imaging. It was found that osteoporosis was identified through the calculating the erosion degree of mandibular lower cortex and mandibular cortical width (MCW) which decrease in females during postmenopausal age (Kwon et al., 2017; Taguchi et al., 2006).

The deep convolutional neural network-based CAD systems were used on panoramic radiographs to identifying osteoporosis. This was evaluated by *Lee etal* in research performed in 2019 and it suggested that early detection of osteoporosis could be facilitated with these technologies.

ML was applied in bone age assessment studies (Dallora et al., 2019). Automatic methods are utilized for identifying areas of interest in wrists and hands on radiographs in order to measure bone age (Larson et al., 2018). Those DL models have demonstrated the capacity to decrease reading time without sacrificing diagnostic accuracy, and for estimating bone age with precision on par with that of a qualified radiologist. (Booz et al., 2020).

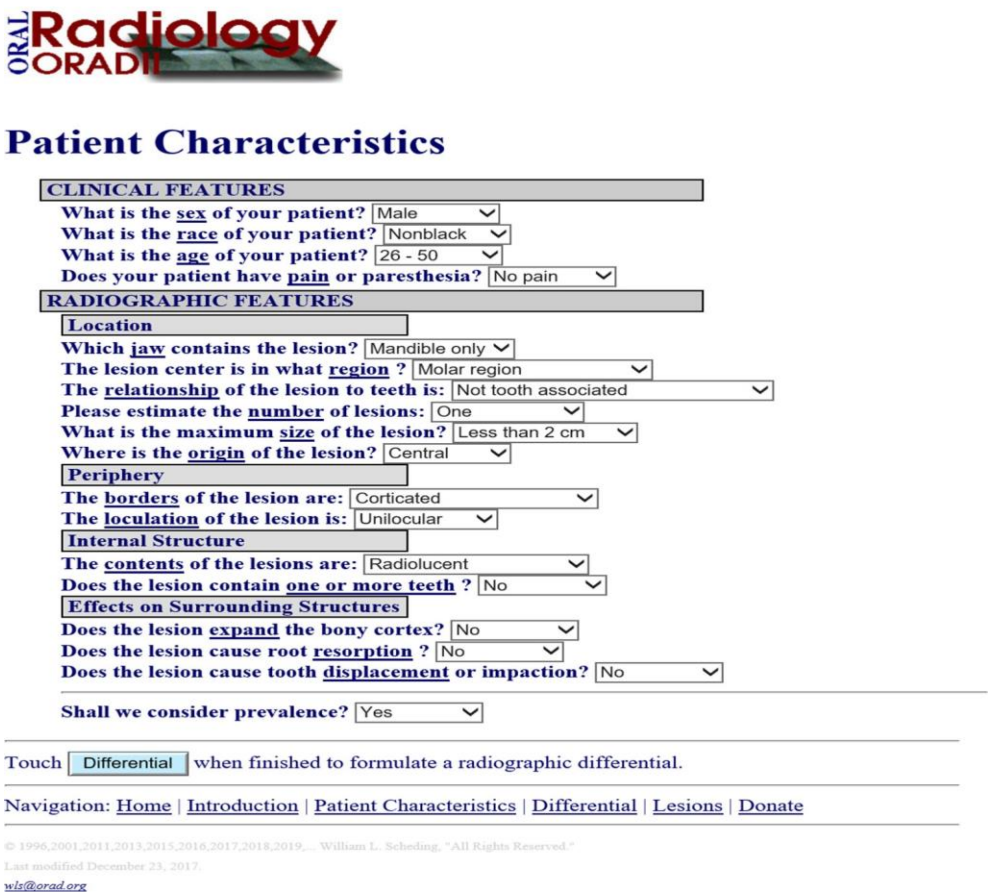

Figure 5. ORAD II web interface (Nagi et al., 2020)

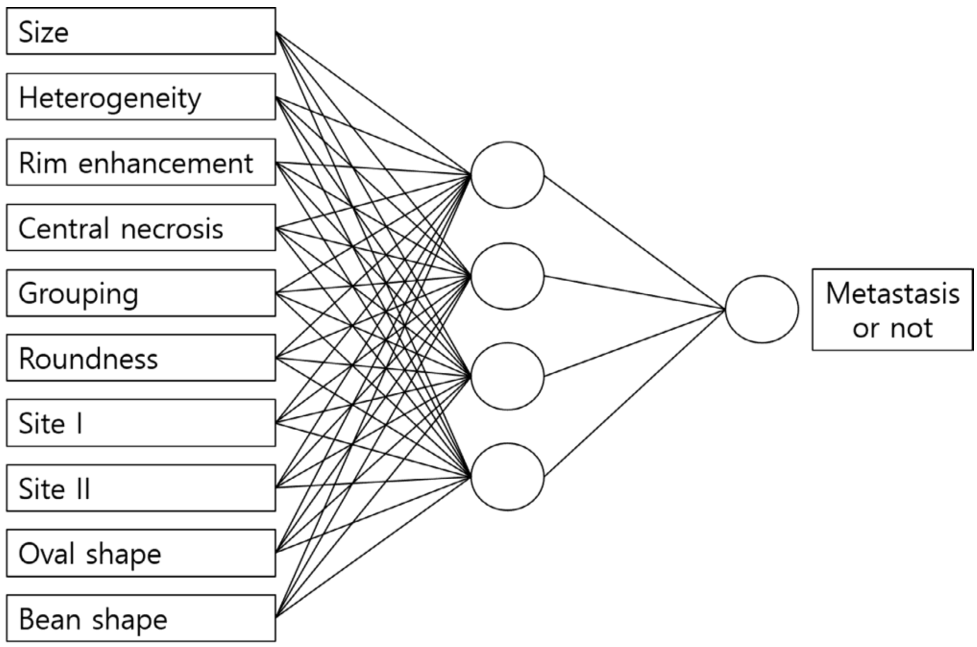

Figure 6. Example of ANN modified by (Park et al., 1999).

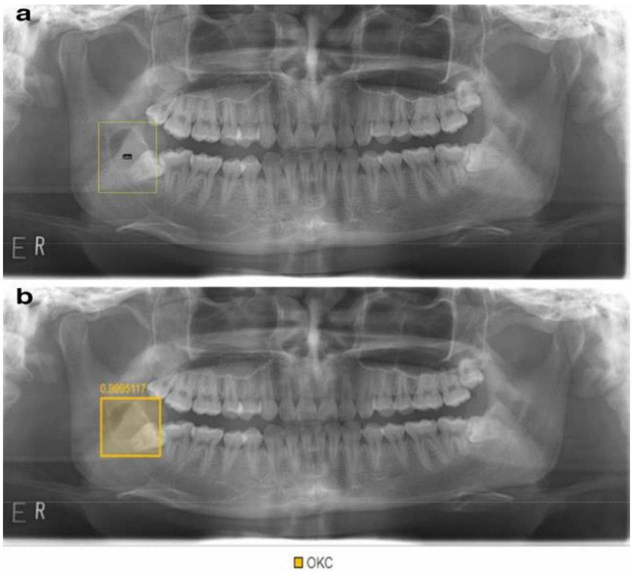

Figure 7a. Odontogenic keratocyst (OCK) is labelled at the right posterior mandible on a panoramic radiograph. b. The lesion has been detected automatically with the use of DL *Heo et al, 2021)*

Cephalometric analyses were carried out using a variety of AI models. But early automated cephalometric analysis techniques have been judged too inaccurate for practical application (Leonardi et al., 2008). New algorithms were created over time to increase accuracy. Latest studies utilizing CBCT images to investigate 3D cephalometric landmark analysis have indicated that mid-sagittal plane landmarks are more reliable than bilateral landmarks (Sam et al., 2019).

6. Forensic dentistry:

Because human teeth develop predictably, forensic dentistry is frequently used for identifying unknown individuals, determine sex, and estimate age. Studies have looked at the information which could be obtained from surrounding bone structures or teeth on dental X-rays. Regrettably, dental X-rays are frequently regarding low quality and may exhibit problems like distortion, superimposition, blurring, and low contrast. As a result, gathering pertinent evidence through clinical procedures might take a very long period, and forensic techniques including tooth measurement could be impacted by the observers' subjective opinions (Ibrahim and Saleh, 2012).

7. Postmortem identification using dental radiography

In the year 2006, Ammar and Nassar created an automated dental identification method that combined bitewing and periapical images, using individual CNNs. In the year 2018, Zhang *etal*. (Zhang *etal*., 2018) presented a teeth recognition label tree with a cascade network that relies on DL methods. According to their results, the method worked better than using a single network. Teeth's developmental as well as degenerative changes, along with those of their supporting structures within the oral cavity, are utilized for estimating age. For both deceased and living patients, dental radiology-based techniques offer a non-invasive and precise substitute for extracting teeth for study. Preprocessing images, classification, feature extraction, and segmentation are some of the steps involved in automated age estimation. Yet, observers could have an impact on the information gathered. DL algorithms, on the other hand, are a significant option for automatic age estimate because they do not need such processes. ANNs were investigated as a potential tool for estimating dental age in canines depending on the pulp-to-tooth ratio (Farhadian et al., 2019). Also in 2019, Mualla et al. showed that a transfer learning approach worked well for age estimation in a different investigation. They used a linear discriminant, decision tree, support vector machine (SVM), and k-nearest neighbor kNN) for classification and AlexNet and ResNet-101 for extracting features from images. Nevertheless, forensic gender determination utilizing dental panoramic radiographs has just been the subject of one investigation to date, and even that work depended on mandibular morphometric data that have been manually collected by observers (Patil et al., 2020). Forensic science depends heavily on radiographic observations of dental structures, like teeth. Yet, because measurements depend on the observer's perception, the procedure is time-consuming and subjective. This issue has a hopeful solution in AI, which makes objective decision-making possible. While age estimation is the primary focus of this research, further advancements in this area could prove to be very advantageous.

8. Image quality improvement:

Because of the transmission and acquisition issues, noise is frequently present in medical images, particularly when using CBCT geometry (Peña et al., 2011; Pauwels et al., 2015). Several ML approaches, such as filtering and sparse-based methods, were tried for image denoising. Those techniques do have certain drawbacks, though, like the requirement for manual parameter tuning or the inability to be used in different contexts. Because of its flexible architecture, DL has lately demonstrated promise in getting over such restrictions. In particular, noise reduction and image deblocking were addressed using generation adversarial network GAN and convolutional neural network CNN architectures. Enhancing the quality of low-dose CT images is one of the main applications of image-denoising technology. Low-dose CT increases image noise even though it minimizes patient exposure, which is advantageous for treatment planning and simulation. DL was used recently to enhance low-dose CT images, and studies integrating DL and ML are currently being conducted to optimize the advantages of the two technologies (Chen et al., 2017). Motion artifacts from the motions of the patient or organs could compromise the accuracy of the diagnosis. Using CNNs to improve the quality of blurry images is being investigated by researchers. AI has also been used to lessen image imperfections caused by metal. Dental implants and crowns are examples of high-attenuation materials that could cause photon starvation, radiation scattering, and beam hardness. These effects could affect the accuracy of diagnosis and produce abnormalities in CBCT and CT images. Conventional metal artifact reduction strategies have been offered in studies for replacing artifacts with surrounding data, yet they have certain limitations in terms of clinical use. Utilizing DL to retrieve data in the artifact area is a more modern method. Furthermore, when the metal portion was removed, images were reconstructed using CNN- or GAN-based image deblocking methods (Zhang et al.,2018).

9. Considerations in artificial intelligence

As was previously indicated, a number of latest investigations in OMF radiology have produced encouraging findings. AI research is still in its early stages and requires careful consideration regarding a number of elements for producing the needed results. A large amount of data is needed to construct AI-based automatic interpretation systems. To enhance the amount of data, this necessitates a proper augmentation procedure. To guarantee that the AI system is learning in the proper way, the training data sets need to have a minimal errors, high precision, and consistency. Thus, it is imperative that OMF radiologists with sufficient experience take part in such initiatives. To accomplish such objectives, precise and effective annotation, drawing, and labeling tools must be created. It is required to have a large-scale dataset with the fine-labeled data annotated through OMF radiologists. Presently, with incomplete studies employing smallscale data, it is difficult to construct DL algorithms effective in clinical dentistry practice. It is imperative that radiographic images be accurately explained, yet there is a global shortage of OMF radiologists with the knowledge and experience required for interpreting radiographic images taken at dentistry clinics. AI could help OMF radiologists manage more images at once, which might be a huge help in addressing this problem. The AI system, for example, is able to classify and pre-identify locations that are suspect. However, because AI readings depend on training data as well as appropriate model selection and training, their outcomes are not totally reliable. Thus, having a final interpretation from OMF radiologists is still crucial. AI makes complicated decisions that are frequently hard for humans to understand. However, it is indefinite to depend on the AI decisions cause when the AI makes incorrect decisions is unknown. Class activation mapping (CAM), Gradient-weighted CAM and guided backpropagation were used to examine and decipher the AI decisions through looking at the radiologist's significant notes. (Selvaraju *et al*., 2020). The reliability of CAM in helping radiologists was evaluated in research accomplished by Kim etal in 2020 that revealed the need for further development and researches to get more explainable AI (Kim *et al*, 2020). It is very important to be aware and prepared for the risks of using AI. Safe and protected usage for the DL-based digital imaging and communication (DICOM) and preventing hacking of these data is redline point since manipulating, adding or removing cancer information is possible in DICOM images which is risky for patients care and safety. So, guarantee the security of DICOM data of patients is highly recommended in hospitals. This is particularly crucial since, according to Desjardins et al. (2014), almost all radiologists (99%) might believe that such changed images are real. In dentistry, radiographic imaging is a very useful tool. It is employed in implant, orthodontic, and oral surgery for both diagnostic as well as appropriate treatment planning purposes. Quantitative analysis related to radiographic images is required in such domains. In such fields, AI is becoming more and more useful. OMF radiologists are specialists who understand the fundamentals and characteristics regarding radiographic imaging. In addition to their expertise in reading radiographs and diagnosing a wide range of disorders, OMF radiography is a vital component of research pertaining to AI and has enormous potential for the advancement of dentistry in future (Desjardins et al., 2014).

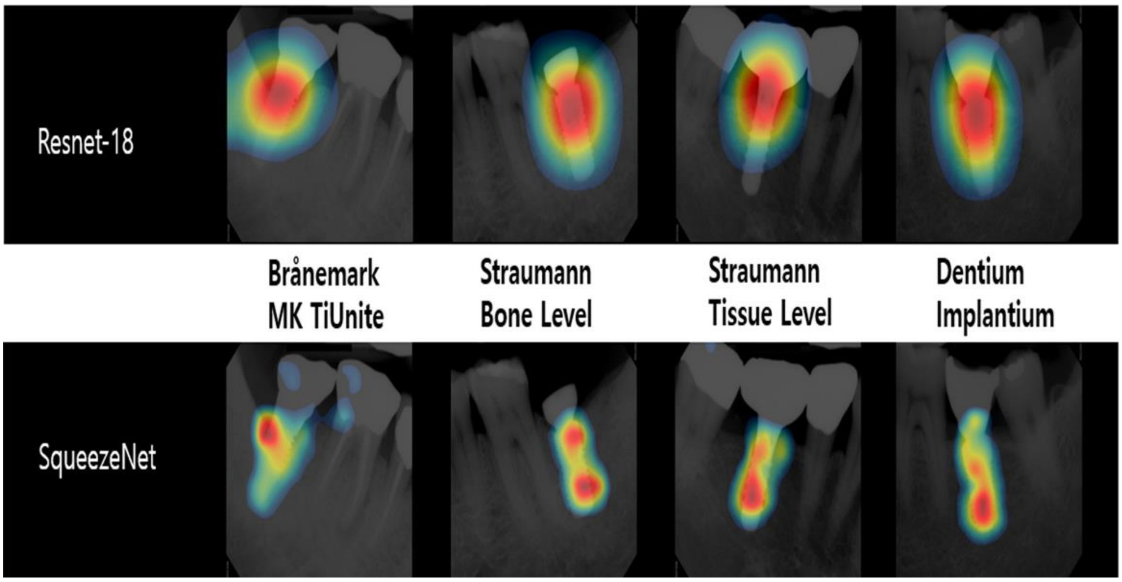

Figure 8 Example of class activation maps of the 5 classification networks for 4 types of implant fixture. When network classifies thetype of the fixture, it determines by looking at specific fixture parts. ***(Kim et al., 2020)***

Conclusion

According to studies on the application of AI in dentistry, NNs have proven to be as accurate and precise as dental specialists. AI technology was outperformed human specialists in certain works. Those results imply that non-specialists and people who are new to the field looking for expert opinions might benefit most from AI applications. AI could be a useful tool for dentists to help with patient information organization and connection building. Also, it can help decrease time and effort spent during and after the dental sessions. It is crucial to remember that in order for a dentist and patient to communicate effectively, it is necessary to recognize nonverbal indications. Such as these technologies that may help as case presentation and provide better understanding for the patients and hence more cooperation to get the best results.

Conflict of interest

Authors have no conflict

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