Artificial Intelligence in Oral Health

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Abstract. Artificial intelligence (AI) has emerged as a transformative force in various fields, including oral health. At the beginning of this chapter, readers are provided with basic information about machine learning (ML) tasks, deep learning models, and selected metrics. In addition, privacy issues and adversarial attacks are briefly discussed before delving into the applications of AI in oral health. The primary objective of this chapter is to review the applications, benefits, and challenges of integrating AI and specifically ML into oral health, including the detection of oral cancers, dental caries, periodontitis and other conditions. The available evidence suggests that ML enables early detection, accurate diagnosis, personalized treatment planning and a better prediction of outcomes. In addition, AI tools reduce the likelihood of human error, thus improving standards in patient care while possibly lowering costs.

Keywords: Oral Health, Machine Learning, Artificial Intelligence, Deep Learning, Dentistry, Oral Cancer, Dental Caries

1 Introduction

Artificial intelligence (AI), especially machine learning (ML) and its sub-field, deep learning (DL), have revolutionised several industries. DL has recently delivered cutting-edge performance in speech processing, text analytics, and computer vision. The widespread use of AI algorithms across many fields has made these technologies indispensable to daily life. Healthcare, a sector historically immune to significant technological upheavals, is now starting to be impacted by AI systems as well [1]. However, their application is associated with several problems and challenges, including safety, privacy and ethical considerations. Another major problem faced in AI applications in healthcare is the limited availability of representative, diverse and high-quality data, which is crucial for training accurate and reliable ML models. The lack of enthusiasm to implement data exchange standards in wider healthcare industry is also hindering the efficacy of ML systems [1].

Recent studies on this topic include a scoping review conducted by Arsiwala-Scheppach et al. [2], published in 2023, which attempted to characterise the overall body of evidence concerning dental ML tasks. The review also assessed types of tasks, their distribution in different dental fields, the risk of bias and reporting quality, as well as the applied metrics. A similar work was done by Leite et al. [3] but it also investigates the applications of radiomics in the field of oral healthcare. The paper emphasizes the promising results achieved through the integration of radiomics and ML, showcasing their ability to improve accuracy, early detection, and personalized treatment strategies.

The objective of this chapter is to conduct a comprehensive review of the applications of AI in oral health. Prior to that, section 2 provides the reader with basic information about ML and DL, presenting common machine learning tasks, DL model architectures and metrics, as well as considerations on privacy and adversarial attacks.

2 Basics of machine learning for medical applications

Massive amounts of data are produced in healthcare, and ML can assist in their processing, which is challenging using “traditional methods”. The benefits of ML and DL have been particularly marked in medical image analysis, delivering human-level performance across various fields, e.g. in clinical pathology, radiology, ophthalmology, and dermatology. Recent breakthroughs in ML techniques have yielded remarkable outcomes in tasks like organ recognition [4], interstitial lung disease classification [5], lung nodule detection [6], medical image reconstruction [7], and brain tumour segmentation [8]. These advancements significantly impacted prognosis, diagnosis, therapy, and clinical workflow.

2.1 Machine learning tasks in medical image analysis

Image analysis is one of the primary applications of ML in the medical field. It aims to support clinicians and radiologists in determining the diagnosis. Various imaging methods can be analysed by ML, e.g. magnetic resonance imaging (MRI), radiography, computed tomography (CT), ultrasound, and positron emission tomography (PET). The tasks performed include image enhancement, detection, classification, segmentation, retrieval, reconstruction, and treatment analysis, as discussed below and summarized in Table 1.

Table 1. Methods in Medical Image Analysis

Task	**Description**
Enhancement	Techniques to improve the quality of medical images for better diagnosis
Detection	Detection and identification of specific abnormalities in medical images

Classification	Categorization of medical images based on specific criteria or classes
Segmentation	Partitioning of medical images into meaningful regions or subjects
Reconstruction	Creation of interpretable images from raw medical data
Report drafting	Report generation from imaging modalities

Enhancement is a critical pre-processing stage of improving the quality of medical images which may be compromised by artifacts and noise, which in turn hamper image analysis. Various DL models are used for denoising medical images, such as *Convolutional Denoising Encoders* and *Generative Adversarial Networks* (GAN) [9]. These methods can also reduce the cost of MRI imaging, as they can obtain Super-Resolution (SR) from low-resolution MRI images which do not require such strong background magnetic field and associated pulse sequences [10]

Detection is the process of identifying specific disease patterns or abnormalities, which conventionally involves expert radiologists and physicians. With a large number of reports to check daily, this requires much time and effort and is also susceptible to human error. On the other hand, DL-based methods have shown high potential in such task, and other ML methods such as *k-Nearest Neighbour* (k-NN) and *Decision Trees* (DT) were also successful in some cases, for example the detection of dermatological diseases [11].

Unlike (object) detection, which includes the localization of a pathology in the analysed image, classification models only determine if the pathology is present or not. The performance of classifiers based on DL, such as *Convolutional Neural Networks* (CNN) has been shown to be superior to other non-learning-based methods. CNNs have been used extensively in recognizing body organs, abnormalities in medical imaging and modality classification [1]. DL models can also be used in a popular technique called *Transfer Learning* [12] – a model pre-trained on a big set of different data is applied and fine-tuned on a relatively modest set of target data, i.e. medical images. Methods like *Synergic Deep Learning* have also proven efficient in medical image classification [13]. A review article by Cai et al. [14] explored the use of transfer learning in image classification for detecting fundus related diseases.

Segmentation is the process of dividing a picture into distinct non-overlapping portions based on pre-defined criteria such as colour, texture, and contrast. In the study of medical image analysis, segmentation is crucial. Sarraf et al. [15] have segmented brain MRIs to facilitate early detection of Alzheimer's disease. Various DL models, such as CNNs and *Recurrent Neural Network* (RNNs), are used for segmentation [16], and several DL architectures are being developed for multi-modal and volumetric image segmentation [17]. Segmentation will be further discussed in Section 2.1.1.

Medical image reconstruction helps generate clear and interpretable images from raw data. By speeding up the traditionally slow process of determining the original system inputs from the output results, DL models aid in the early detection while also saving time and reducing storage requirements. As an example, GANs were employed for the reconstruction of motion-corrupted brain MRI [18], a simplified scheme of the process is presented in Figure 1.

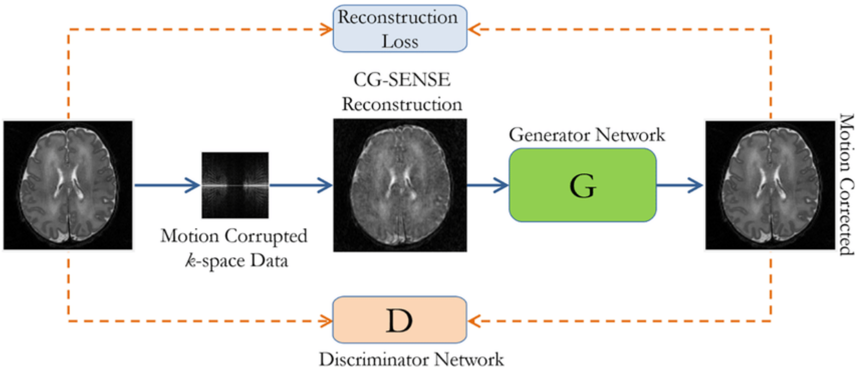

Fig. 1. Reconstruction of motion-corrupted images using GAN [21].

Lastly, DL can be used for drafting the reports of image analysis. Writing the reports is very time-consuming and tedious, and it may be difficult for inexperienced radiologists and pathologists or even for experienced experts under time pressure. Various researchers have attempted to resolve this issue with the help of *Natural Language Processing* (NLP) models, which can be used to annotate clinical radiology or pathology reports. Besides, DL architectures like *Long Short-Term Memory* (LSTM) network, CNNs and RNNs are developed for automatic report generation. Figure 2 shows a report generated for chest X-rays. [19]

Impression: No acute cardiopulmonary abnormality.

Findings: There are no focal areas of consolidation. No suspicious pulmonary opacities. Heart size within normal limits. No pleural effusions. There is no evidence of pneumothorax. Degenerative changes of the thoracic spine.

MTI Tags: degenerative change

Fig. 2. Frontal chest X-rays of a patient, alongside the findings and annotated tags [20].

2.1.1 Comparison of Object Detection and Segmentation

Object detection is a computer vision technique that deals with locating object instances in images or videos [21]. *You Only Look Once* (YOLO) and *Deep Residual Networks* are widely-used DL architectures for object detection, while popular training datasets include COCO, ImageNet etc.

Segmentation categorizes the image at pixel level. *Semantic segmentation* classifies the pixels based on their semantic meaning, treating all objects within a category as one entity, as opposed to *instance segmentation*, which differentiates between individual instances of the same category, enabling more accurate identification of objects.

Many real-world applications utilize semantic segmentation, such as self-driving cars, pedestrian detection, and diagnostic purposes. Other DL systems can use this pixel-level semantic data to grasp spatial positions and make judgements [22]. A popular segmentation model called *U-Net* was created for biomedical image segmentation and used for example in a study of oral lesions [23], where segmentation was performed along with object detection using YOLO. Figure 3 illustrates the differences between object detection and semantic segmentation.

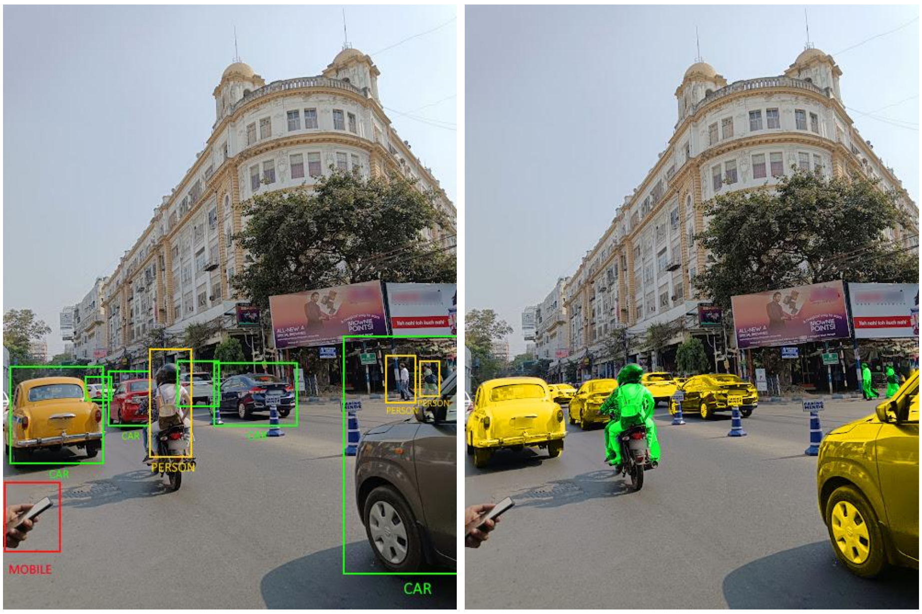

Fig. 2. On the left, object detection localizes the different objects in the scene using a bounding box. On the right, semantic segmentation labels every pixel of the identified objects but has no notion of separate instances of the same entity.

The applications of instance segmentation include robotics, autonomous self-driving surveillance, medical diagnosis etc. [17]. A common instance segmentation framework is Mask R-CNN [24]. For each object instance, it predicts a bounding box, a class name, and a pixel-level mask. The Detectron2 model developed by Facebook was used to construct Mask R-CNN with three distinct *ResNet Feature Pyramid Network* (FPN) backbones.

2.2 Deep Learning Architectures

In this subsection, DL architectures including DenseNet, ResNet, U-Net, Mask R-CNN, and YOLO (Figure 4) will be presented in detail, as they have been demonstrated to be very successful in various oral health applications.

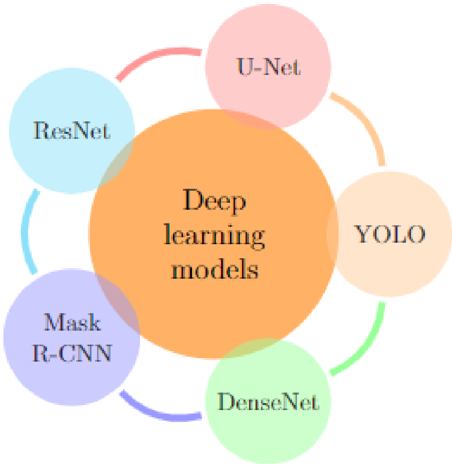

Fig. 4. DL architectures frequently used in oral health.

DenseNet, an abbreviation of *Dense Convolutional Network*, is a deep learning architecture that has gained significant attention and popularity in computer vision. DenseNet differs from traditional CNNs by introducing direct connections between every layer, creating a densely connected network. These connections enable each layer to receive direct input from all preceding layers, resulting in feature reuse and enhancing gradient flow. This architecture promotes more robust feature propagation, encourages feature extraction at multiple scales, and improves overall network efficiency. DenseNet has demonstrated impressive performance on various visual recognition tasks, often achieving state-of-the-art results with fewer parameters than other models. Its dense connectivity and efficient parameter usage make it an appealing choice in all computer vision tasks. Figure 5 presents a diagram representing the DenseNet architecture.

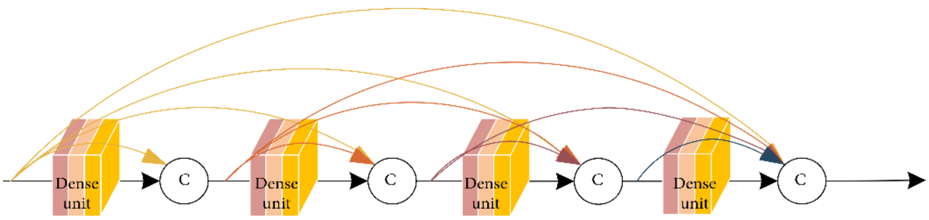

Fig. 5. A dense connection mode [25].
Image source - https://www.hindawi.com/journals/bmri/2022/2384830/fig7/

ResNet, short for *Residual Neural Networks*, was proposed by He et al. [26] and has since become a cornerstone in many state-of-the-art image classification and object recognition tasks. Traditional deep neural networks suffer from the degradation problem, where the model's accuracy decreases as the depth increases. ResNet addresses this issue by introducing skip connections that allow information to flow directly from one layer to another, bypassing a few intermediate layers. ResNet allows the training of very deep neural networks with hundreds or even thousands of layers (Figure 6).

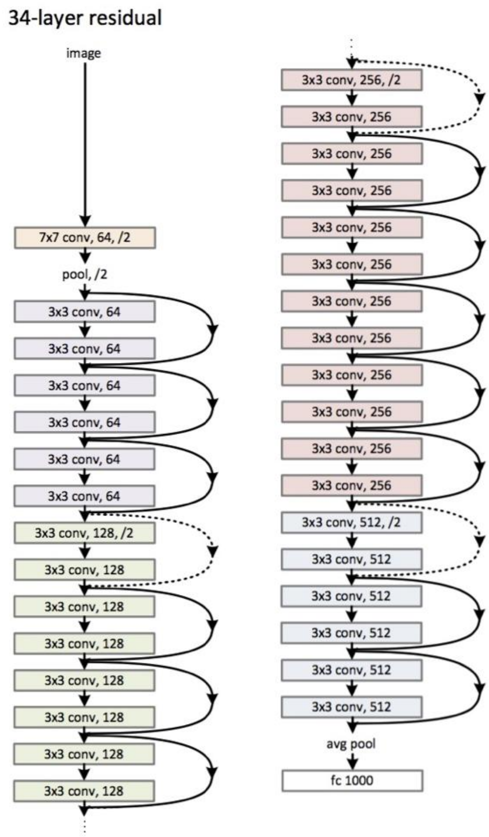

Fig. 6. ResNet architecture [26].

U-Net is a widely used CNN architecture designed specifically for image segmentation tasks. U-Net’s name is derived from its U-shaped architecture, which consists of an encoder path and a corresponding decoder path. The encoder path performs downsamplingoperations to extract high-level features and capture contextual information from the input image. The decoder path then uses upsampling and skip connections to recover spatial information and generate segmentation masks with fine-grained details. The skip connections enable the network to fuse low-level and high-level features, facilitating precise localization of objects. Figure 7 depicts the U-net architecture.

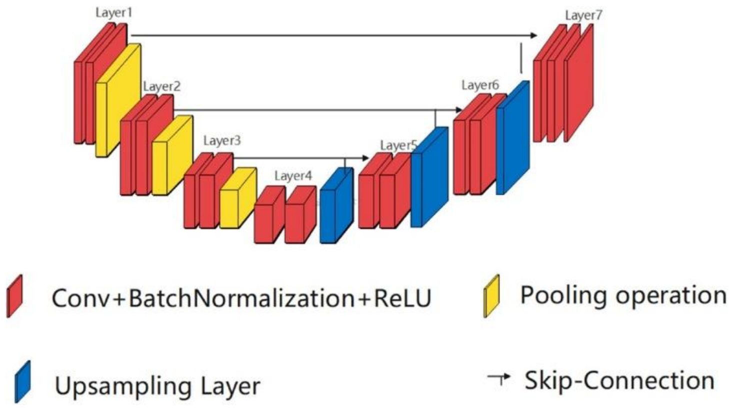

Fig. 7. Structure of U-Net architecture [27]

Mask R-CNN, i.e. *Mask Region-based Convolutional Neural Network*, is a state-of-the-art DL model that combines object detection and instance segmentation abilities. The model consists of two main components: a region proposal network (RPN) that generates potential object regions and a network head that simultaneously predicts bounding box coordinates, class labels, and object masks. By incorporating a fully convolutional network into the architecture (Figure 8), Mask R-CNN enables accurate instance segmentation while maintaining real-time inference speeds.

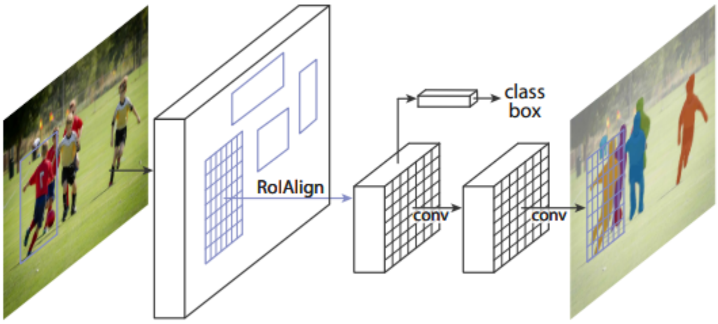

Fig. 8. Mask R-CNN framework [17].

YOLO, *You Only Look Once* in full, is an object detection architecture that has gained popularity for its real-time performance and high accuracy. It was introduced by Redmon et al. [28] in 2015. The key idea behind YOLO is to approach object detection as a single regression problem. The image is divided into a grid and a CNN predicts bounding boxes and class probabilities for each grid cell. As a result, YOLO performs object detection in one pass and simultaneously operates on the entire image, making it highly efficient. Figure 9 is a simple representation of how YOLO architecture works.

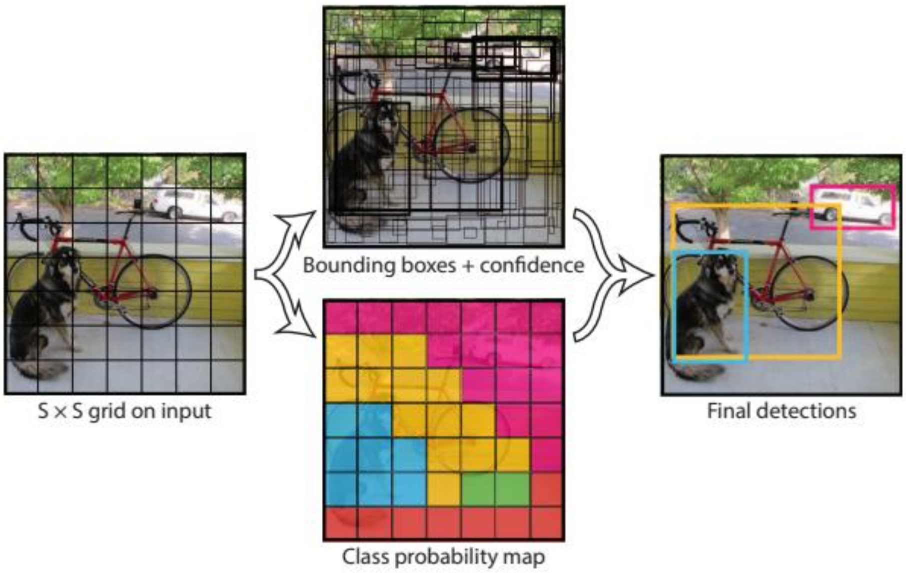

Fig. 9. YOLO architecture [28].

2.3 Selected metrics used for the evaluation of deep learning models

The performance of object detection and segmentation models is commonly assessed using the average precision (AP) metric [21], which is defined as the area under the precision-recall curve. Precision, which corresponds to the positive predictive value, is the ratio of true positives (TP) to the sum of TP and false positives (FP), while recall (sensitivity) is the ratio of TP to the sum of TP and false negatives (FN).

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

For a prediction to considered as TP, the predicted class must be correct and the intersection over union (IoU) between the ground truth and the prediction must exceed a certain threshold. If the predicted class is inaccurate or if IoU drops below the threshold, the prediction is categorised as FP. On the other hand, FN predictions mean that an object was not identified despite being present in the image. With these defined, AP can be calculated using the following equation:

$$AP = \sum_{n} (R_n - R_{n-1}) P_n$$

where P_n is the precision at the n^{th} threshold, while R_n and R_{n-1} are the recall values at the n^{th} and $(n-1)^{th}$ threshold, respectively.

Other common metrics include accuracy, the F1 score, which is the harmonic mean of precision and recall, and the Dice score, also known as the Dice Similarity Coefficient.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

$$Dice\ score = \frac{2TP}{2TP + FP + FN}$$

2.4 Privacy Considerations and Adversarial Attacks

Along with the benefits posed, AI comes with privacy challenges and ethical considerations. Understanding these concerns and potential malicious events, as well as developing robust safeguards is crucial for harnessing the full potential of AI while protecting patient rights and maintaining trust in oral healthcare systems.

ML relies upon vast data, including sensitive personal information, and respecting individuals' privacy rights and obtaining proper consent for data usage is paramount. The ethical aspects are discussed in Chapter 10, so this section will focus on the robustness and safety of ML models in terms of privacy and adversarial attacks, which are often not sufficiently considered. Existing works on privacy protection can be classified into three groups, based on the role of ML in privacy [29]:

1. **Privacy of data for ML models**. This includes making both the input and output data, as well as ML model parameters private throughout the process, as the privacy threat may appear at any stage. Most of the research investigated the use of differential privacy in ML and DL models.
2. **ML-enhanced privacy protection**. Works in this group employ ML models as a tool for improving privacy protection.
3. **ML-based privacy attack**. In contrast to the previous group, ML can also be used as an attacking tool. Especially DL systems may surpass conventional privacy-preserving methods, necessitating a discussion of such new threats and corresponding solutions [30].

The classification is further expanded in Figure 10.

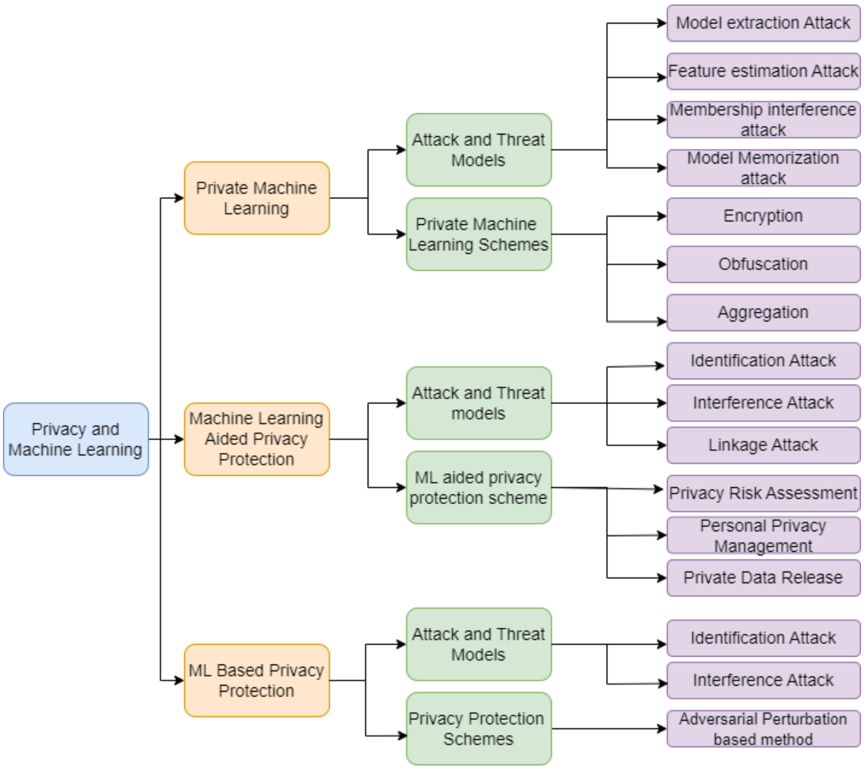

Fig. 10. The proposed taxonomy of privacy and ML [31]

Adversarial attacks involve deliberately crafting subtle input perturbations to deceive ML models into making incorrect predictions, highlighting their vulnerability in robustness. Figure 11 shows how perturbations can confuse the AI model and affect its final output.

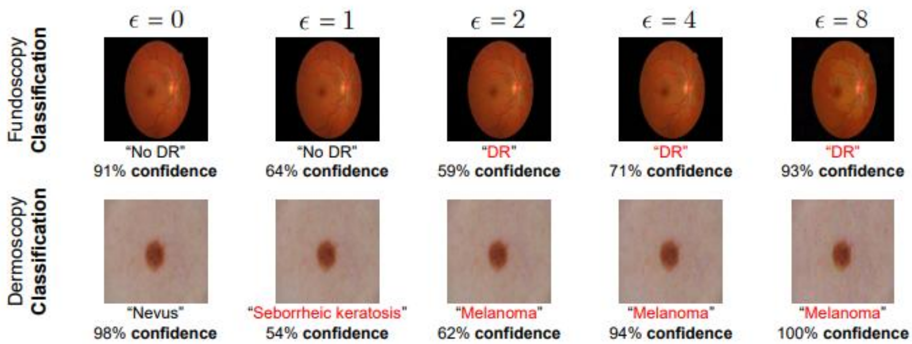

Fig. 11. Visualizing a medical adversarial example with predictions under different perturbations sizes ϵ. Predictions labelled in red indicate incorrect predictions. [32]

The success of adversarial attacks is due to the lack of generalization in the low probability space of data [33]. Some popular adversarial attacks proposed for natural images and applied to medical images include the *Fast Gradient Sign Method* (FGSM), *Basic Iterative Method* (BIM), *Projected Gradient Descent* (PGD), *Jacobian-based Saliency Map Attack* (JSMA), and *Universal Adversarial Perturbation* (UAP). In some studies, however, these adversarial models are intentionally incorporated into the trained DL models [31], because adversarial training is one of the most effective approaches to defending against adversarial attacks [34]. As a result, the DL models trained on a mixture of clean and perturbed data become more resistant to adversarial attacks.

3 Applications of Machine Learning in Oral Health

Just like medicine and other fields, oral health is undergoing a revolutionary transformation thanks to the quick development of ML and AI in general. AI enables the extraction of significant insights from oral health records, photographs, and other relevant sources by leveraging the power of algorithms and large volumes of data. In the coming sections, we will review a few ML applications in oral health and how they could contribute to improving oral health outcomes, enhancing patient care, and shaping the future of dentistry.

3.1 Applications in Oral Cancer Diagnosis

Oral cancer has become a serious global public health concern. Squamous cell carcinomas (SCCs), which are aggressive malignancies with a high propensity to spread locally and distantly, account for most oral cancers. It has also been observed that oral SCC (OSCC) has considerable implications on patients' post-treatment quality of life due to its location and the disease's aggressive attitude. Considering the commonly delayed diagnosis of oral cancer, the 5-year overall survival rate is roughly 51.7 % [35].

Cancer treatment is mainly dependent on tumour staging. However, discrepancies in staging methods have contributed to inaccurate prognoses in OSCC patients. ML algorithms can offer valuable support to clinicians by providing them with more precise and comprehensive diagnostic and prognostic information. A paper by Huang et al. [36] proposed a new optimized CNN model for the diagnosis of oral cancer. Another recent study presented an ML model for the prediction of oral cancer in patients with oral leukoplakia and oral lichenoid mucositis [37], which accounts for age, sex, tobacco usage, alcohol consumption, diabetes status and 10 other parameters. This proves that by leveraging large data sets and analysing complex patterns and features within histopathological images and patient data, ML can assist clinicians in making early informed decisions regarding appropriate treatment strategies, ultimately leading to improved survival rates for oral cancer patients.

AI not only changes the scope of screening and enhances accessibility to early cancer detection but may further enhance diagnosis due to its accelerated workflow and accuracy compared to traditional human screening techniques. For instance, AI does not suffer from observational fatigue, and compared to the naked eye, it is able to notice minute changes in the range of a single pixel at a higher rate [38].

3.1.1 Classification of Oral Lesions

Oral cancer is frequently preceded by visible oral lesions known as *oral potentially malignant disorders* (OPMDs) that can be recognised during a clinical oral examination. The likelihood of malignant transformation associated with OPMDs makes their early identification crucial for lowering oral cancer morbidity and mortality. Oral lesions have a very heterogeneous appearance, which makes it difficult for healthcare practitioners to identify them and that can delay patient referrals to oral cancer experts.

Recent advancements in computer vision have opened new possibilities for developing technologies that can automate the screening of the oral cavity. These technologies can provide real-time feedback to healthcare professionals during patient examinations and enable individuals to perform self-examinations. The existing literature on image-based automated diagnosis of oral cancer has primarily emphasised using specialised imaging techniques like *optical coherence tomography*, *hyperspectral imaging*, and *autofluorescence imaging*. These advanced imaging modalities offer unique capabilities for capturing detailed information about the oral tissues and detecting potential abnormalities or early signs of cancer. There are also attempts to detect and classify OPMDs using ML in photographs [22]. This problem can be formulated as a classification, object detection, as well as segmentation task (Figure 12), and various DL architectures have been tested, including *ResNet-152*, *DenseNet-161*, *Inception-v4* and *EfficientNet-b4* [39]. Regardless of the modality, image analysis using DL algorithms can provide a useful second opinion for non-expert clinicians, assisting them in making timely and informed decisions regarding patient care [40].

Fig. 12. Different types of image recognition tasks showing semantic segmentation (left), instance segmentation (centre) and object detection (right) [38]

3.1.2 Cancer detection using breath samples

Exhaled breath analysis is another interesting field of research. The method assesses exhaled breath for volatile organic compounds (VOCs) which serve as biomarkers for many diseases and metabolic conditions. Gas chromatography combined with mass spectrometry is used to analyse VOCs, but other methods, such as proton transfer reaction mass spectrometry have been tested as well [41]. The advantages of this method for disease identification and monitoring include non-invasiveness, cost-effectiveness, and real-time point-of-care disease diagnosis.

In relation to OSCC, electronic nose technologies, such as *Near-Infrared Optical Nose* (NIRON), have been able to distinguish OSCC, lung cancer, and a control group based on VOCs in breath samples [42]. A recent study investigated the possibilities of ML techniques, such as *multilayer perceptron* (MLP) and *probabilistic neural networks* (PNN), in electronic nose technologies for the detection of oral cancer [43]. ML techniques were also used for the identification of signature biomarkers of OSCC among compounds detected using gas chromatography and mass spectrometry to distinguish OSCC patients from healthy smokers [44].

3.1.3 Tumour classification based on genetic data

Prior to cancer treatment, the histopathological analysis is performed to confirm the diagnosis, as well as for staging and grading. However, some tumours with the same histopathological classification can exhibit varying responses to the proposed therapy. This discrepancy can be attributed to genetic variations and environmental factors that lead to alterations in the biological behaviour of cancer cells. Therefore, there is a growing need for diagnostic models that incorporate genetic characteristics alongside morphological features, enabling the prediction of the biological behaviour of the cancer and hence enhancing treatment selection [45]. A recent study examined such models to improve the efficiency of personalized cancer treatment [46]. The ML diagnostic tool performed exceptionally well in the diagnosis of OSCC, and it also showed that gene expression is a more important element in classifying cancer types than its histological traits. Figure 13 shows the workflow of the study [46] and Table 2 summarizes relevant research papers on the use of ML in oral cancer and OPMDs.

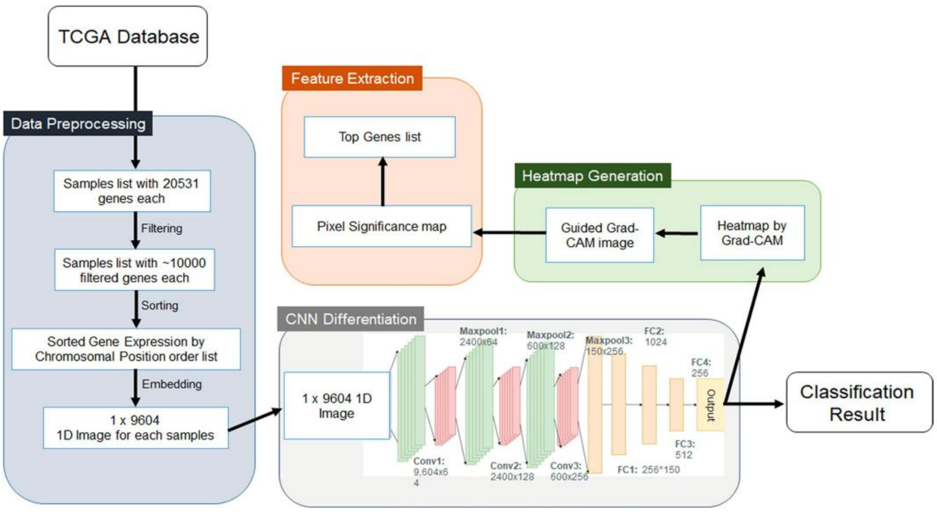

Fig. 13. Workflow of the study by Pratama et al. [46].

Table 2. Overview of papers regarding oral cancer

Year	Author	Summary	ML architecture used
2020	Kowalski et al. [35]	Survivability of Oral cancer	
2020	Kar et al. [38]	AI and Oral Cancer screening	DCNN,CNN,SVM,DBN
2020	Tanriver et al. [40]	Detection of oral lesion with DL	U-Net, R-CNN,YOLO
2020	Welikala et al. [23]	Classification of Oral Lesions	R-CNN,ResNet,RPN
2020	S.Das et al. [41]	Viability of Breath Analysis	
2021	Mentel et al. [44]	Breath analysis for oral cancer diagnosis	kNN,LR,RF
2021	Pratama et al. [46]	Oral cancer and gene expression with ML	CNN
2023	Adeoye et al. [37]	Prediction of Oral cancer with ML	SVM,MLP,LDA
2023	Bhatt et al. [45]	Cancer detection from genomic data	SVM,kNN,CNN
2023	Huang et al. [36]	Diagnosing Oral cancer with DL	CNN

3.2 Diagnosis of Dental Caries

Dental caries is one of the most prevalent diseases in the world. Caries is characterized by the localised destruction of dental hard tissues by acidic byproducts of bacterial fermentation of dietary carbohydrates. Both the crown and the root of teeth can be affected by caries [47], and if not treated, caries can ultimately result in tooth loss and a decline in quality of life [48]. On the other hand, timely detection of caries can reduce the invasiveness of the treatment or avoid it entirely [49]. ML can be used either for the detection of caries in images, or to predict its development from demographic data [50]. Table 3 shows some recent works related to the diagnosis and treatment of dental caries, and the topic is further addressed in Chapter 7 dedicated to the use of AI in cariology.

3.2.1 Detection of Dental Caries in Radiographs

Radiographs are crucial especially in approximal caries detection, as proximal tooth surfaces can hardly be visualised otherwise [51], and a growing number of studies using AI to identify caries have been recently published [52]. For example, Lee et al. developed a U-Net model for identifying dental caries from bitewing radiographs [53]. Without any pre-processing, the bitewing radiographs were used to train the CNN model, and it was confirmed that the proposed model could aid dental professionals in making more accurate diagnoses of dental caries in real-world clinical situations. In another study, Lian et al. [49] developed a model employing nnU-Net and DenseNet121, which was used to classify lesion progression after the nnU-Net technique had segmented the carious lesions. Finally, the authors introduced a dropout mechanism and label softening to address the overfitting phenomena during model training, ensuring that it achieves the greatest potential performance. While there were many other studies on caries detection in radiographs and other images, e.g. photographs, it is beyond the scope of this chapter to examine them in detail.

3.2.2 Prediction of Dental Caries from Demographic Data

As dental caries is a highly prevalent oral disease, its prediction is a crucial aspect of preventive dentistry. Clinical evaluation and risk assessment are the mainstays of conventional procedures. However, the use of demographic data to forecast the risk of dental caries has become more popular with the development of ML.

Kang et al. used the data obtained from the 2018 Korean Children's Oral Health Survey and analysed them using various models including *Gradient Boosted Decision Tree* (GBDT), *Random Forest* (RF), *Logistic Regression* (LR), *Support Vector Machine* (SVM), and LSTM [54]. The models performed well and could be used as a diagnostic tool to find individuals affected by caries. Additionally, the models can offer helpful guidance for creating a plan to prevent and treat caries, which can significantly decrease the time required for patient diagnosis and expenditures associated with caries.

Toledo et al. proposed to use ML and predictors gathered from a 10-year prospective cohort study performed in children aged 1 to 5 years in southern Brazil to construct a caries prognosis models in primary and permanent teeth [55]. The development of caries was initially investigated in 2010 and then again in 2012 and 2020. As a part of the study, information on behavioural, clinical, psychological, psycho-social, and demographic aspects were collected. LR was used along with the DT, RF and extreme gradient boosting (XGBoost). All models exhibited an area under the ROC curve (AUC) above 0.70 in predicting primary tooth caries after a two-year follow-up, with baseline caries severity being the best predictor [55].

Table 3. Recent works on dental caries using ML models.

Year	**Author**	**Summary**	**ML models Used**
2021	Lian et al. [49]	DL in Caries Detection and Classification	DenseNet, nnU-Net
2021	Lee et al. [53]	Early Caries Detection using radiographs	U-Net, R-CNN,YOLO
2022	Reyes et al. [48]	ML in Diagnosis and Prognosis of Dental Caries	-
2022	Kang et al. [56]	Prediction of Caries using ML and Personalised medicine	ANN, CNN, LSTM
2022	Talpur et al. [57]	ML algorithms in diagnosis of caries	-
2023	Martins et al. [52]	ML in X-Ray diagnosis for oral health	-
2023	Toledo Reyes et al. [55]	Early Childhood Predictors for Dental Caries	LR, RF, XGBoost, DT

2023	Kang et al. [54]	Dental Caries Prediction Model Using ML for DSS	GBDT, RF, LR, SVM, LSTM

3.3 Other applications

The applications of ML in oral health encompass a diverse array of topics, showcasing the versatility and adaptability of ML algorithms in addressing numerous challenges faced by dental professionals and researchers. By harnessing the power of AI, these applications aim to augment traditional dental practices, improve clinical decision-making, optimize treatment strategies, and enable more personalized and effective patient care. In this section, we will explore AI applications in other dental fields, and as in previous sections, Table 4 shows an overview of selected studies in these fields.

3.3.1 Periodontitis

Periodontitis is another highly prevalent oral condition caused by bacterial biofilm, but it is also affected by genetic and environmental factors, particularly cigarette smoking [58]. Periodontitis is a common cause of tooth loss in adult and elderly patients, because it gradually destroys the periodontal connective tissue and bone support. Furthermore, periodontitis is associated with various systemic diseases and an increased risk of cancer [50], making its prevention, timely diagnosis and adequate management highly important not only for oral health.

In 2020, Chang et al. [59] created a DL hybrid method for automatic periodontitis staging based on bone loss in panoramic radiographs. The proposed hybrid framework combined a DL architecture for bone level detection and traditional *Computer-Aided Diagnosis* (CAD) processing for classification. The overall intraclass correlation coefficient value between the generated model and radiologists' diagnosis surpassed 0.9, indicating very accurate automatic periodontal bone loss diagnoses.

Other studies used ML techniques for predictive modelling. Nasir et al. [60] used American and Taiwanese national survey data and explored potential periodontitis predictors shared between the two datasets. Ten machine learning models were trained to predict the presence of periodontitis, which included AdaBoost, *Artificial Neural Networks* (ANNs), DT, Gaussian process, k-NN, linear support vector classification, linear discriminant analysis, LR, RF, and Naïve Bayes. The obtained results concluded that the ANN model had a high accuracy. In another study, Troiano et al. [61] designed and validated models for the prognostic prediction of molar survival after periodontitis treatment. Along with LR, they also built models based on SVM, k-NN, DT, RF, ANN, Gradient Boosting and Naïve Bayes. All the models showed promising results with an AUC value over 0.7. An ensemble method combining LR with neural networks reached an AUC of 0.759, making it the most reliable algorithm in the three validation cohorts.

Kim et al. [62] proposed an alternative approach, developing an ML model for chronic periodontitis prediction based on salivary bacterial copy number, which was measured in healthy individuals and patients with chronic periodontitis using PCR. Based on the severity of periodontitis, they used ANN, SVM, LR, and RF to identify bacterial combinations that could serve as a biomarker for periodontitis diagnosis and staging. Figure 14 depicts the ML workflow of this study. Further information on the use of AI in periodontology can be found in Chapter 4.

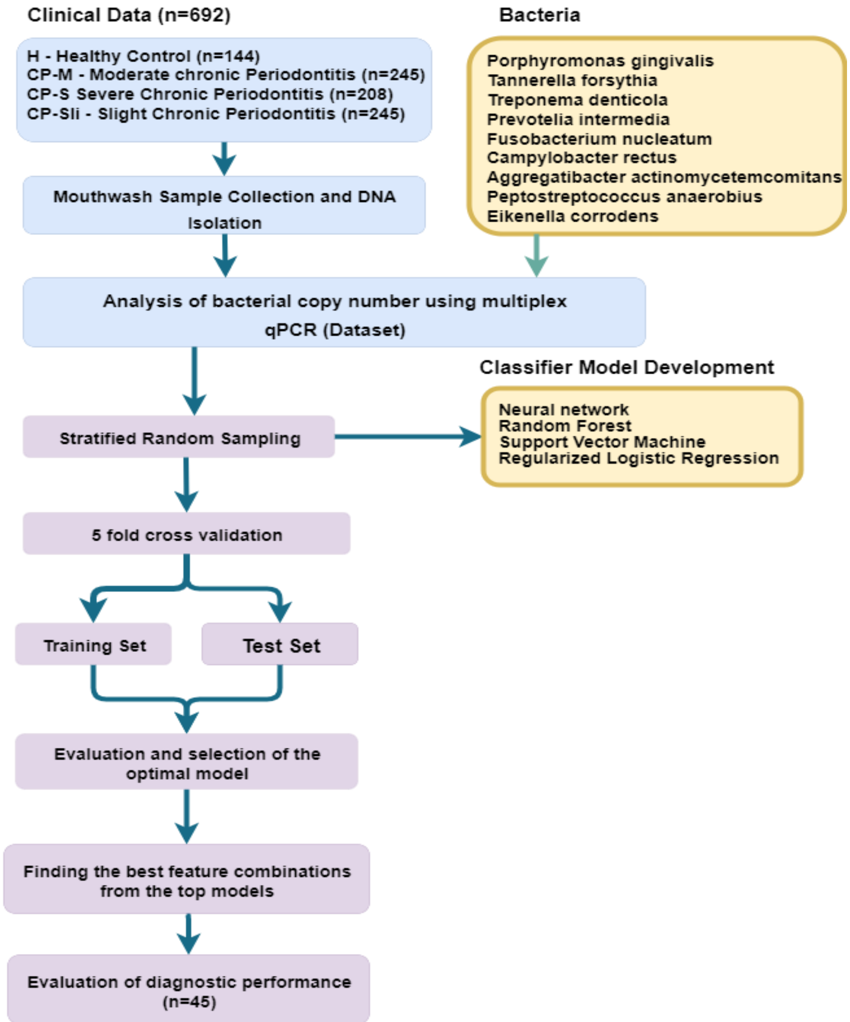

Fig. 14. ML workflow for the prediction of chronic periodontitis severity using qPCR data [62].

3.3.2 Endodontics

In endodontics, pulpitis, pulp necrosis, and apical periodontitis represent the main causes for root canal treatment. Applications of ML in this field include examination of teeth anatomy, evaluation of the treatment difficulty or the detection and classification of periapical radiolucencies.

As an example of root anatomy examination, Hiraiwa et al. [63] successfully used a DL system to determine if a second distal root is present in mandibular first molars. The analysis was done on apical radiographs, and cone-beam computed tomography (CBCT) was used as a gold standard. The analysis of root anatomy is also a part of the treatment difficulty assessment, which is usually done following the Endodontic Case Difficulty Assessment Form by the American Association of Endodontists [50]. Mallishery et al. [64] built an SVM model to assess the treatment difficulty using this form. The model had a sensitivity of almost 95 %, and it was concluded that the automated difficulty assessment could increasing the speed of decision-making and referrals if necessary.

Other studies focused on periapical lesions in radiographs and CBCTs. For instance, Orhan et al. [65] employed a deep CNN to locate periapical lesions in CBCT scans and calculate the lesion volume, achieving promising results. Some researchers aimed at a clinically difficult task of differentiating periapical granulomas from radicular cysts in CBCTs [66] and panoramic radiographs [67]. Both the referenced studies showed excellent results, which could lead to a more efficient referral strategy and subsequent treatment efficacy. A thorough overview of AI applications in endodontics is available in Chapter 8.

3.3.3 Orthodontics

Orthodontic treatment involves straightening or repositioning teeth in order to improve occlusal function as well as aesthetic appearance. Applications of AI in orthodontics can improve the efficiency of treatment planning, and some of them are outlined in this section. For more details, please refer to Chapter 6.

Prior to the treatment, orthodontist thoroughly analyse the clinical situation and radiographs to compile a suitable treatment plan. Several studies used DL architectures for landmark detection in cephalometric analyses. However, there were also studies which focused on the analysis of soft tissues in facial images. Rao et al. [68] developed a facial landmark recognition model based on the *Active Shape Model* (ASM) model and the YOLO architecture, which was more accurate in facial landmark detection and measurement compared to their manual assessment.

ML techniques may also help in choosing whether to extract premolars in cases with malocclusion that includes severe tooth crowding. Jung and Kim [69] developed a back-propagation neural network-based model for diagnosing extractions, which had a success rate of 93 % in distinguishing extraction and non-extraction cases. In another study, Leavitt et al. [70] attempted to develop a generalizable ML algorithm from a large sample of orthodontic providers to accurately predict orthodontic extraction patterns in a racially and ethnically diverse populations. In total, 55 cephalometric and demographic data were provided to the ML models based on RF, LR, and SVM. The results differed for various extraction patterns, so were successful while some were rather inaccurate.

With the expansion of digital dentistry, tooth segmentation in 3D models has become increasingly important in orthodontic treatment planning and outcome prediction. Tian et al. [71] suggested a method that makes use of sparse voxel octree and 3D CNNs, which offered segmentation accuracy of 89.8 %. In a similar task, Xu et al. [72] created a 2-level hierarchical CNN framework that labels the teeth, gingiva, and spaces between the teeth. The boundary was then fine-tuned using improved fuzzy clustering. For the segmentation of CBCT scans, Pei et al. [73] successfully applied the 3D exemplar-based random walk, as its results agreed with manual segmentation, while Juodzbalys et al. [74] developed a novel DL method for tooth labelling in 3D intraoral scans.

3.3.4 Dental Implantology

Dental implants serve as a support for restorations of missing teeth, thereby playing a a crucial role in restoring function, aesthetics, and oral health in general. The placement of a dental implant is influenced by various factors such as bone density and anatomical structures, as well as oral and general health. All these factors must be carefully assessed to ensure optimal outcomes, in which advanced AI technologies can assist by analysing imaging data, predicting potential complications, and providing precise treatment planning tailored to the patient's unique conditions.

In image analysis, several studies investigated the localization of anatomical structures, e.g. the mandibular canal. Its position is important during implant placement as it contains the inferior alveolar nerve and any damage to it could have long-term or permanent impact on the patient. In one of the studies, Kwak et al. successfully detected and segmented the mandibular canal on CBCT images using U-Net [75]. Image analysis can also be used to determine the amount and quality of the available bone and its mineral density. For example, Sorkhabi et al. suggested using a CNN to assess alveolar bone density in 2019 [76].

Based on the provided data, ML can be also used to model treatment outcomes. Liu et al. [77] created an ML model that estimates the implant failure rate using the DT, SVM, LR and classifier ensembles based on bagging and AdaBoost. It was concluded that the model can help surgeons by choosing the optimal implant system and prosthodontics treatments for their patients [77]. Another insight was brought in the study by Ha et al. which indicated that the mesio-distal position of the inserted implant is the most significant factor determining its prognosis [78]. Further studies on the topic, as well as other uses of AI in dental implantology are presented in Chapter 5.

3.3.5 Dental Age Estimation

Dental age is thought to be a quick, precise and trustworthy method of age determination in growing children. In orthodontics, planning the treatment of various malocclusions is closely related to the stage of maxillofacial growth. In paediatric dentistry, dental age may be also important in certain cases, e.g. related to irregular tooth eruption. And skeletal growth is also relevant for prosthodontics and implant planning in adolescent patients. Besides dental applications, dental age estimation is also important in forensic medicine, anthropology and bioarchaeology, as it may provide information about earlier populations [79].

Over the years, several radiographic techniques for estimating dental age have been developed. These methods essentially identify the stages of tooth development in radiographs (Figure 15) and code them in accordance with the readily available tables created by various authors. The best-known of these are the Willems method, the Nolla method, the Haavikko method, and the Demirjian method. Recently, Cameriere's novel strategy has received a lot of attention and favour [79].

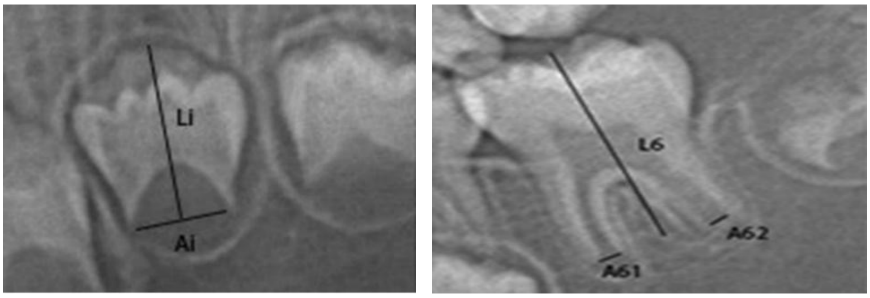

Fig. 15. Example of single and multiple root teeth measurement [80].

Researchers have used the help of AI in estimating the dental age. One such study was conducted by Aljameel et al. [81] who used four CNN architectures and observed that the further they reduced the age range of the experiment, the finer the models learned and functioned. Shen et al. [82] constructed three ML models, namely LR, RF and SVM, to estimate children's dental age using the Cameriere’s method and to compare them with the Cameriere’s formula. The results showed that the SVM, LR, and RF models were more accurate than the conventional approach represented by the Cameriere’s formula. This outcome encourages the use of ML techniques for dental age estimation.

Table 4. Selected works related to ML in the other dental fields.

Year	Author	Summary	ML model used
2020	Sun et al. [50]	ML applications in stomatology	-
Periodontitis			
2023	Troiano et al. [61]	LR and ML model for prediction of Molar Loss	LR, SVM, ANN, RF, DT, Naïve Bayes
2022	Bashir et al. [60]	Comparison of ML models for periodontitis prediction	-
2022	Chang et al. [83]	DL for radiographic diagnosis of periodontitis	CNN
2020	Chang et al. [59]	DL hybrid method for PBL	CNN
2020	Kim et al. [62]	Prediction of Periodontits from Bacterial Copy number	RF, SVM, LR
Endodontics			

2023	Ver Berne et al. [67]	Classification of radicular cysts and periapical granulomas	MobileNet, YOLO
2020	Orhan et al. [65]	Detecting periapical pathosis on cone-beam CT scans	CNN
2020	Mallishery et al. [64]	Difficulty assessment using ML	SVM
2019	Hiraiwa et al. [63]	Recognition of dental root structure from radiographs	AlexNet, GoogleNet
2015	Okada et al. [66]	Diagnose dental periapical lesions in cone beam CT scans	LDA-AdaBoost classifier
Orthodontics			
2023	Leavitt et al. [70]	Prediction of orthodontic extraction patterns	RF, LR, SVM
2019	Rao et al. [68]	Facial landmark recognition model	ASM, YOLO
2019	Juodzbalys et al. [74]	Automatic labelling teeth using dental surfaces from 3D intra oral scanner	MeshSegNet
2019	Tian et al. [71]	Automatic classification and segmentation of 3D dental model	CNN
2018	Xu et al. [72]	3D tooth segmentation and labelling	CNN
2016	Pei et al. [73]	Segmenting Come-beam CT images	Random Walk
2016	Jung and Kim [69]	Model for diagnosis of extraction	Back propagation neural network
Dental Implantology			
2020	Kwak et al. [75]	Mandibular Canal detection	CNN
2019	Sorkhabi et al. [76]	Classification of alveolar bone density	DT, AdaBoost
2018	Liu et al. [77]	Predicting failure of dental implants	CNN
2018	Ha et al. [78]	Factors influencing prognosis of dental implants	KLMS, FEM
Dental Age Estimation			
2023	Aljameel et al. [81]	Dental Age Estimation using AI	CNN
2021	Shen et al. [82]	ML assisted Cameriere method	LR, RF, SVM

4 Conclusion

ML has emerged as a powerful tool in oral health, offering significant potential in various aspects of diagnosis, personalised treatment planning and prediction of outcomes. This is achieved using various ML techniques, which can analyse clinical records and patient data, as well as DL models frequently used for image analysis and other tasks. However, the widespread adoption of AI in oral health also raises significant concerns in terms of ethics and privacy, and attention also must be paid to adversarial attacks. Addressing these challenges requires collaborative efforts of all stakeholders to develop robust safeguards for the responsible use of AI in dentistry.

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