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A comprehensive survey of deep learning algorithms and applications in dental radiograph analysis

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ABSTRACT

The Integration of machine learning and traditional image processing in dentistry has resulted in many applications like automatic teeth identification and numbering, caries, anomaly, disease detection, and dental treatment prediction. They have a broad scope in different applications observed in the dentistry literature review. This study reviews the literature on deep learning and dental radiograph analysis. We present an overview of machine learning algorithms in different areas of dentistry: tooth identification and numbering, Dental disease detection, and dental predictive treatment models. The methods under each area are briefly discussed. The dental radiograph data set required for performing experiments is summarized from the available literature. The study concludes by discussing new research opportunities and initiatives in this field. This paper offers a comprehensive overview of this innovative, challenging, and growing area in dentistry.

1. Introduction

The progress in the area of dentistry using basic image processing and deep learning techniques is tremendously increased. They have broad scope in different applications of dentistry that had been observed in the literature review of dentistry. The deep learning techniques are integrated with computer-assisted diagnosis (CAD) in many applications of dentistry. The automated dental radiographs analysis will assist the dentist in improving their daily workflow.

In the last two decades, there has been a substantial increase in digital technology in dentistry. The scarcity of medical and dental personnel in most emerging countries fuels demand technology, particularly artificial intelligence software [1]. Costs, time, the requirement for human knowledge, and the frequency of medical errors can all be reduced due to this.

Artificial intelligence (AI) is a field in computer science that has achieved significant advances in medicine, and there is an emerging body of AI study in dentistry. The distinct abilities of dentists and AI systems have the potential to improve patient care. Artificial intelligence-based solutions will improve patient care by freeing the dental personnel of mundane tasks, improving population health at lower costs, and eventually facilitating personalized, predictive, preventative, and participatory dentistry [1]. Recently, an increase in the use of computer-assisted analysis of dental radiographs in dentistry from the researchers is observed. The key reason for this is that it may effectively eliminate manual errors and human-made errors caused by stress, exhaustion, or a lack of expertise. Furthermore, it minimizes diagnosis time, improving the dental care system's overall efficiency and accuracy [2].

Researchers are working in this subject and doing their best to develop the most reliable ways due to the current demand. It has been noted that a huge number of research articles in this topic have been published by authors from all over the world. Based on the research work done different areas of dentistry had identified and Fig. 1 shows in general the number of research papers published in these areas of dentistry using deep learning algorithms.

Radiographs are the primary tool for dentists using which they can analyze the tooth structure. Dr. Otto Walkhoff took the first original dental roentgenogram from a part of a glass imaging plate in his own mouth in January 1896 for a 25 m exposure time. Since then, dental imaging has advanced tremendously, and its applications in numerous sectors of dentistry have increased [3].

Fig. 2 shows different radiograph types such as occlusal, bitewing, periapical and panoramic radiographs [4]. A big portion of a dental arch can be seen on an occlusal radiograph. They focus on children's teeth development and placement. Each X-ray shows nearly the whole arch of teeth in either the upper or lower jaw. Bitewing radiography provides a detailed view of the upper and lower teeth through one area of the mouth. Each bitewing depicts a tooth from the crown (visible surface) to the level of the supporting bone. The entire tooth is captured on a periapical X-ray. Everything is visible from the crown (chewing surface) to the root (below the gum line). A little piece of upper or lower teeth is seen on each periapical X-ray. These X-rays are

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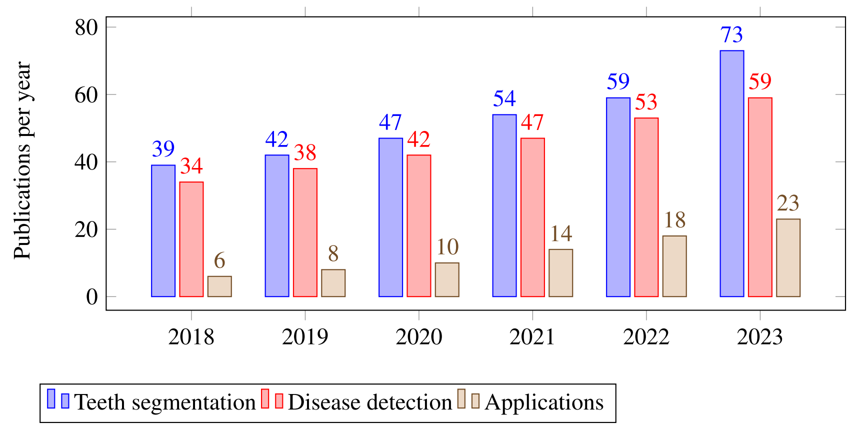

Fig. 1. Publications on dentistry over last five years.

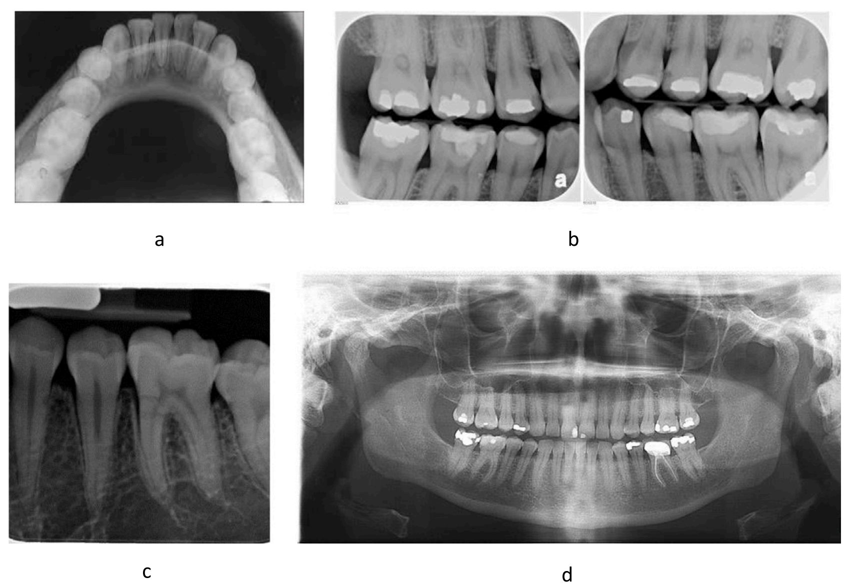

Fig. 2. Types of radiographs (a): Occlusal radiograph, (b): Bitewing radiograph, (c): Periapical radiograph, (d): Panoramic radiograph [4].

often used to detect any unusual changes in the root and surrounding bone structures. Since its introduction in the 1950s, panoramic imaging has grown in popularity and importance as a diagnostic tool. It is a specialized tomographic technique for creating a flat representation of the jaws' curving surfaces. They are preliminary screening radiographs, used to evaluate the dentition and bone support, locate impacted teeth, and see where dental implants are placed [3].

In the practice of competent dentistry, dental radiography is the principal diagnostic tool. Because of the excellent provision and placement of machines and processing equipment is simple to use during dental procedures. Dentists can also detect disorders such as tooth fractures, abrasions, dental caries, attrition, gingivitis, periodontal disease, abscess, interdental bone loss, supernumerary teeth, impacted teeth, cysts, cancers, developmental defects, impending malocclusion, and so on [5]. As a result, experts can detect issues with the tooth, mouth, and jaw. Dental radiographs are used to aid in this process.

The use of dental radiography is increasing all the time, so it is more important than ever to assist dentists with computer-aided analysis; eventually, the efficiency of dental treatment will improve. Nowadays, digital radiographs are playing an essential role because of their better image quality than conventional radiographs. Also, digital radiographs are commonly used because of their advantages like no chemical required for development, the ability to take images instantly, lower radiation dosages, good quality of images, speed, and less storage capacity [6]. Visual examination by dental care professionals during dental treatment is insufficient to determine the cause of a range of dental problems. It is because they are found in mineralized tissues like bone and teeth. As a result, digital radiographs are required during dental treatment. Dental radiographs provide several advantages, including immediate digital image availability, low radiation exposure, and the ability to use image processing techniques such as image enhancement, image restoration, image analysis and image registration [7].

In everyday clinical practice, dental radiograph analysis is an essential aspect of the diagnosis process. An expert's interpretation comprises tooth detection and numbering. Radiographs are essential data sources for diagnostics in dentistry. The photographic record of an image made by passing an X-ray source through an object is known as radiography. X-ray images are used in dentistry to examine the status of a patient's teeth, gums, jaws, and bone structure. Without dental radiographs, dentists would not be able to detect many dental disorders until they were severe. In view of this, the radiographic examination aids the dentist in identifying the source of the problem early on, enabling them to devise the most effective treatment plan for the patient [5].

1.1. Role of enhancement in analysis of radiographs

In many hospitals and clinics, radiography is commonly employed in dentistry observation and treatment evaluation. Radiographic images

Fig. 3. General steps involved in radiograph enhancement.

are generated by X-ray radiation traveling through the oral structure at varying levels according to the organ density, resulting in various image greyscale levels. According to the American Dental Association, the X-ray radiation intensity is kept as low as possible, at 0.150 mSv, to avoid damaging dental and organ tissue in the mouth [8]. Various factors, like the device utilized, the acquisition procedure, and the subsequent processing of the received images, can impact dental radiographs. Because this form of image is a two-dimensional representation of a three-dimensional object, the various anatomical structures are superimposed in the images obtained. The radiographic image produced is frequently of poor quality due to the low intensity of X-ray radiation used on purpose to avoid health problems and restricted instrument capabilities. Radiographic pictures with noise, low contrast, and unacceptable brightness levels make it difficult for doctors to analyze dental radiographs (periapical, bitewing, panoramic), especially during clerkships in dental hospitals [9]. This majorly affects the evaluation of the dental treatment because it is mainly done by observing information of filling's condition, pulp tissue, dentin thickness, periodontal ligament, and lamina dura from dental radiographs [10]. As a result of non-uniform brightness and poor contrast in the collected images, intelligent robots and expert systems used in dentistry experience recognition and identification challenges [11].

The image quality obtained is key to its successful interpretation. The use of preprocessing procedures like image enhancement has contributed to increase machine learning model's output accuracy. Researchers have devised many techniques for it, like boosting contrast and brightness, contrast limited adaptive histogram equalization (CLAHE), other denoising filters artifact reduction, and minimizing noise as shown in Fig. 3 [12]. Diverse digital images with various visual characteristics can be created depending on the application of image processing algorithms. These diverse methods can improve diagnostic performance and subjective image quality by increasing images contrast [9]. The use of preprocessing procedures has contributed to increase machine learning model's output accuracy. Image enhancement techniques can be divided into two categories: spatial and frequency domain.

New enhancement techniques must be developed that are capable of improving radiographic picture quality by addressing all of the issues, allowing the images to deliver more helpful information to clinicians, and facilitating radiographic image review. Radiographic image processing has become a significant subject of automation in dentistry, as radiograph interpretation is a crucial aspect of diagnosis, dental health monitoring, and treatment planning.

The vast dental radiograph dataset needs to be annotated before using it to develop deep learning algorithms. A ground-truth dataset is a shared dataset that has been annotated. Annotations can be drawn boxes over radiographs, written language denoting samples, a new spreadsheet column, or anything else the deep learning program should learn to give output. The most typical uses of radiograph annotation are to distinguish objects and borders and to segment images for purposes such as meaning or whole-image understanding. Radiograph annotation is also known as tagging, transcribing or data labeling. A large amount of data is required to train, evaluate, and test a deep learning model for each of these applications. Junior doctors are concerned to annotated the dataset. Different annotation techniques like bounded box are observed in the literature review. As per the literature review, several methods are available for uniquely numbering the teeth. Most of the researchers had used these method for annotation of their data set by clinician experts.

1.2. Methodology

Areas identified: Innovative computer approaches are being applied in commercial manufacturing and university research, which are applicable in a wide range of dental specialties. This is beneficial to both the digitization of dentistry and the expanding therapeutic and diagnostic needs. In many areas of dentistry, such as teeth numbering and identification, caries detection, diseases, and anomaly detection, orthodontics, and maxillofacial surgery, as well as periodontics and prosthetics, only an accurate diagnosis provides the optimal treatment plan, which is the only method to rebuild the patient's health. Although the specialist's diagnosis and treatment plan are based on his or her knowledge, there is a high possibility of inaccuracy due to various factors like low level of experience, fatigue and other personal factors . As a result, multi-parametric pattern recognition technologies (statistics, machine learning, and artificial intelligence) show much potential for doctors and patients.

According to literature analysis and a keyword search approach, a few primary topics were identified and classified under several dental domain applications. However, widespread adoption of clinical decision support systems (CDSS) in dental practices is still a long way off, requiring development in various areas, including methodological and technological issues. The article gives a rundown of the most recent AI-related research and clinical dentistry initiatives.

How areas are identified: The different areas are identified based on the research work done using image processing tools and deep learning architectures in dentistry. The primary analysis of dental radiographs required teeth identification and numbering as per standard methods.

Research questions:

1. What are the different areas in dentistry where deep learning can be used?
2. What are the different methods/approaches available for teeth numbering and identification?
3. What are the different techniques used for radiographs enhancement and segmentation?
4. What are the different anomalies and diseases can be detected using dental radiographs analysis?
5. What are the different dental treatment prediction systems developed using deep learning?

1.3. Search strategy

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach was used to conduct the literature search [13] as depicted in Fig. 4. 'Image processing in Dentistry,' 'use of deep learning in dentistry', 'dental radiographs analysis,' 'dental disease detection using artificial intelligence, are the keywords or keyphrases that were employed in the earliest stages of this review. The set of keywords was increased hierarchically as the survey progressed. More search phrases were examined as more appropriate publications were discovered.

The PRISMA approach's four-phase flow labeled "Identification", "Screening", "Eligibility", and "Included" was utilized as a model for narrowing down a considerable number of publications. The search strategy of this literature review study includes a platform of digital libraries like Scopus, IEEE explores, Pubmed, Google scholar, Wiley, Science direct, and Researchgate. The search was initiated with the keywords mentioned in the earlier text. The prisma flowchart shows

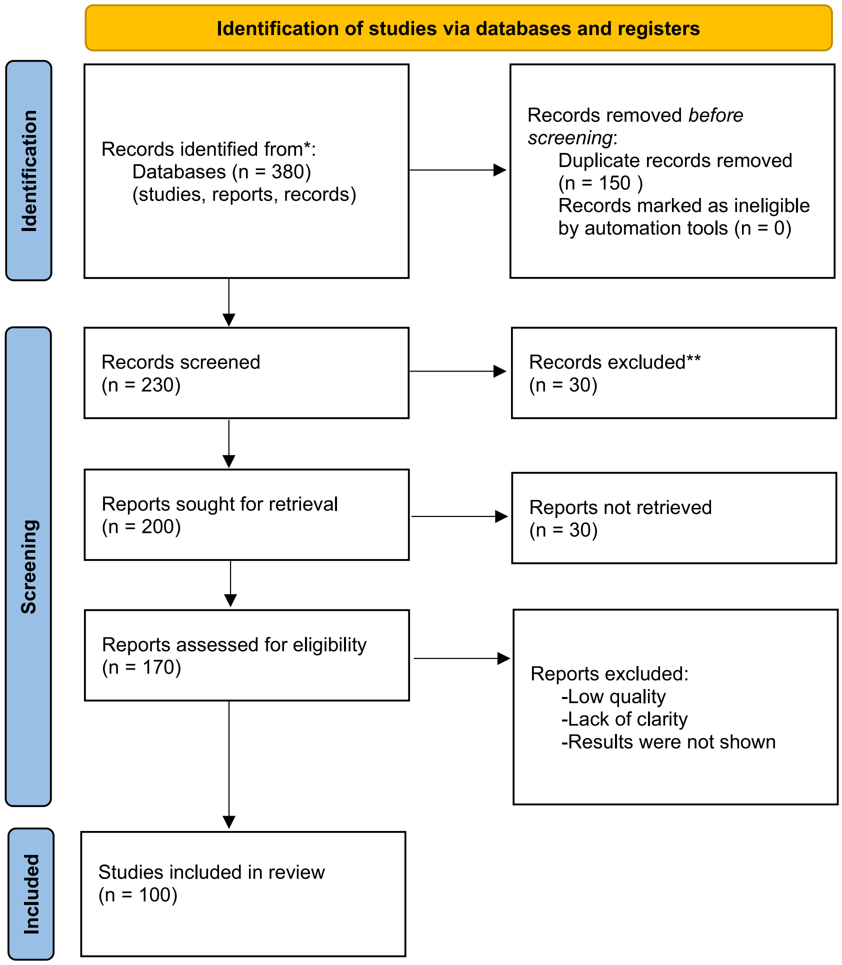

Fig. 4. PRISMA phases [13].

the search strategy applied to review the recent work done in dentistry under different digital library platforms. Also, the search was narrow down to a data set related to radiographs. All the research articles included in the study are from the year 2010 to 2023. Literature survey shows that research that took place in dentistry using deep learning is increasing day by day. Research published in 2020 is tremendously increased as compared to the last few years. Different types of variables used in each study were also identified. The most commonly used variable category is teeth, dental caries, lesions, etc. The most common data set type used is panoramic and periapical radiographs.

The publications have been checked to ensure that they are eligible for inclusion. Some papers, for example, were duplicates, while others mentioned dentistry but not in sectors connected to dentistry shortlisted applications were removed. Out of a vast initial collection of papers, 100 publications were eventually chosen for investigation in this study. This number was later increased to references, which were used in this research.

Different research areas in dentistry are classified as shown in Fig. 5. Dentists use tooth numbering to signify and specify information associated with a specific tooth. Using a tooth numbering system makes it simple to identify patients, communicate with them, and keep their dental records. Tooth numbering serves a variety of uses, including clinically and radiographically identifying and classifying the condition linked with the affected tooth. This allows dental practitioners to communicate efficiently in order to assess and treat oral problems. There are various distinct tooth numbering schemes used around the world. It has been observed that the main areas of dentistry research is teeth identification and numbering as it helps in many applications further. For example, human identification in forensic reports. Also, these finding helps in further diagnosis of diseases related to particular tooth and early detection of major diseases. Hence dental disease is classified as the second central area in dentistry research work. Dental diseases on which researchers used deep learning algorithms are categorized in three major areas: caries detection, anomaly detection, and primary disease detection like oral cancer or osteoporosis.

Using deep learning (DL), computers may be able to provide clinical diagnosis and therapy recommendations in dental applications. DL has been used to diagnose and predict diseases, as well as offer therapy suggestions, due to its capacity to detect linkages and patterns in enormous amounts of data. As per the literature review, it is also observed that many dental treatment prediction models had developed based on the dental radiograph analysis and with the use of deep learning algorithms. Fig. 6 illustrates percentage wise publications in different areas of dentistry.

1.4. Motivation

The automatic dental care assistant model may help dentists by improving the efficiency of their daily workflow. Analysis of dental radiographs gives essential information to clinicians to understand overall oral health and diagnosis problems related to it. Further, detecting dental caries, anomalies, and diseases at an early stage is still challenging for dentists. Nowadays, computer-assisted diagnosis (CAD) tools are integrated with machine learning techniques, which give good results in dentistry. However, few areas still need attention to promote the involvement of machine learning research in dental radiology. Also,

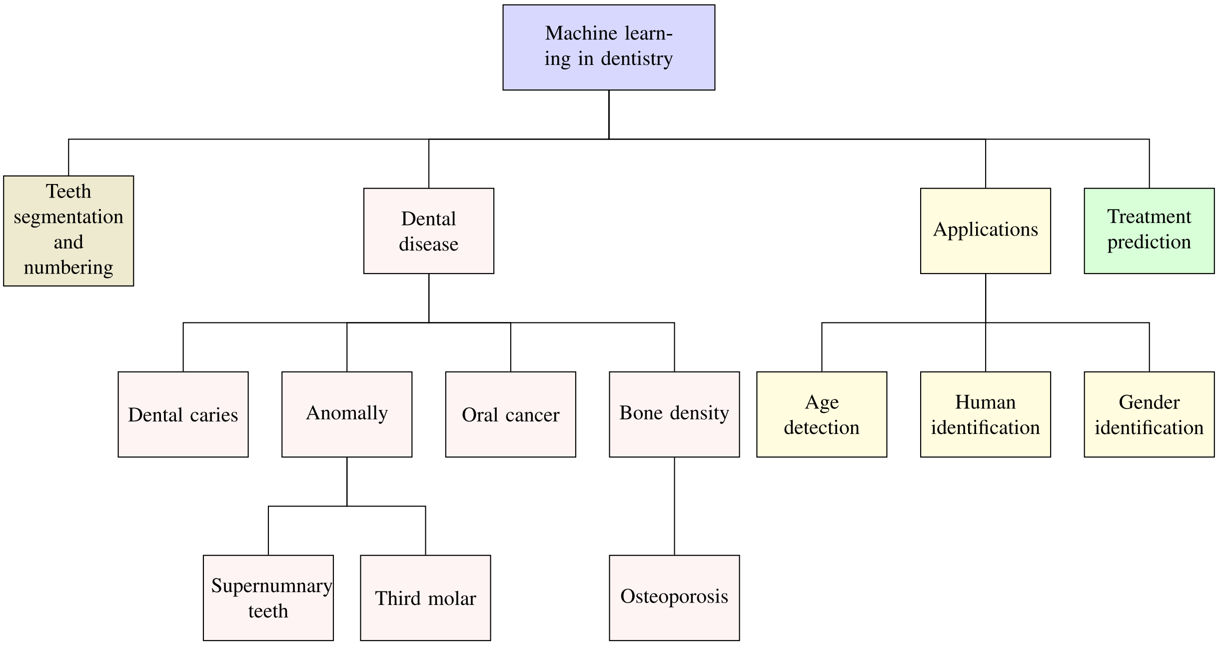

Fig. 5. Different research areas of dentistry.

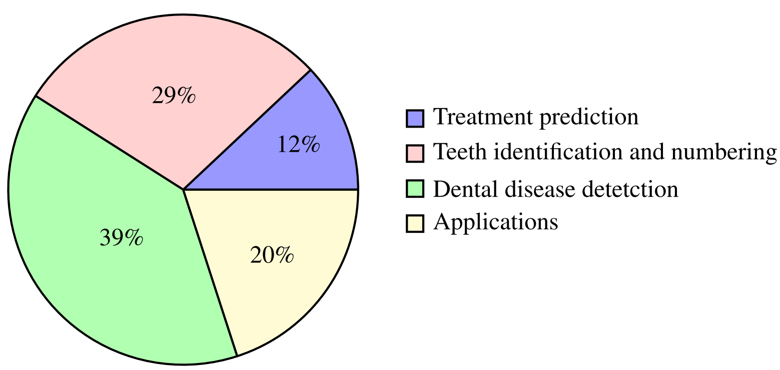

Fig. 6. Percentage publications in different areas of dentistry.

it is observed that more research is required in the use of convolutional neural network's (CNN's) models to improve accuracy in order to consider for everyday practice. Efforts are required to create the public dataset and data standardization for deep learning applications in dentistry. Many studies used a small data set, and accuracy is not up to the clinically expected levels [1].

Dentists would not be able to discover many dental diseases without X-rays until they become severe. As a result, the radiographic examination aids the dentist in identifying the source of the problem early on, making it possible for them to devise the most effective patient's treatment plan.

A dataset is a collection of data samples. The majority of the studies reviewed are deal with modest data sets, in the range from 1 to 100 radiographs on average. The research work with more than 500 radiographs is either not openly available or comprises radiographs that vary only in tooth count [14]. Deep learning models were unable to comprehend all of the subtleties of the teeth intrinsic edges and borders due to a lack of training dental radiographs.

We have aimed to include the extensive research conducted in the field of dentistry using deep learning. We believe that, to the best of our knowledge, all significant datasets and dental radiograph enhancement techniques are provided alongside their sources and were used by researchers to conduct experiments. All of the information tabulated in this article will help future researchers to make informed selections about the approaches to use for their projects.

This study includes importance of automation in analysis of dental radiographs. It all covers different methods used for primary task such as teeth identification and numbering. Also summarizes the use of deep leaning in detection and prediction of different dental diseases. Finally, with this survey we aim to:

1. Highlight how deep learning techniques have infused dental radiograph analysis;
2. Discuss different dental radiograph enhancement techniques and available dental radiograph datasets;
3. Identify the challenges to successfully applying deep learning in dental radiograph analysis;
4. Illustrate particular contributions that exploit or eliminate these challenges;
5. Showcase the novel opportunities of deep learning in dentistry;

The remainder of the article is organized as follows: Section 2 introduces different learning techniques for teeth identification and numbering. Section 3 highlights the different dental diseases detection by analyzing dental radiographs. Section 4 summarizes the use of AI and DL in different dentistry applications. Section 5 discussed treatment prediction. Section 6 introduces some ways to deal with the limited

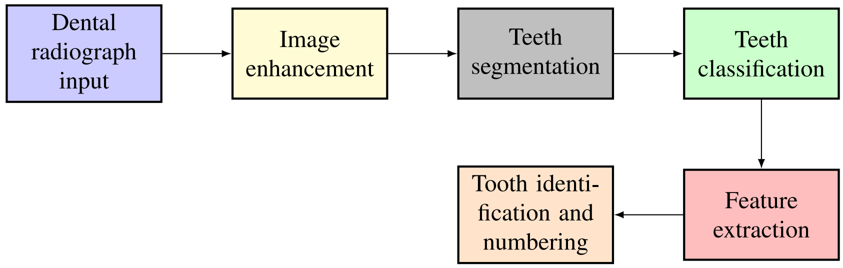

Fig. 7. Generalized block diagram for teeth identification and numbering.

available data set and lists the publicly available data set. Finally, the discussion and conclusion are provided in Sections 7 and 8.

2. Teeth identification and numbering using deep learning

The research area of dentistry needs adaptive approaches and faster techniques of teeth identification and numbering, which is the primary stage in any diagnosis. The research has attempted to explore the possibility of designing practical algorithms that are general enough to be applicable in teeth segmentation, identification, numbering, caries detection, anomaly, and disease detection as well as in different applications of dentistry.

The primary analysis of the teeth requires teeth numbering and identification as per standard methods of teeth numbering. When a dentist uses radiographs to diagnose a patient's problems, the shape, quantity, and position of teeth are the most important factors to consider. In reality, the primary purpose of segmenting and recognizing teeth in images is to make other automatic approaches easier to use in subsequent processing steps as shown in Fig. 7.

Teeth extraction or segmentation is the technique of separating part of the image from a dental radiographs containing some other undesired portions of the mouth, such as gingivae or jawbones, each bearing the borders of one tooth [15]. Tooth segmentation gives essential information to clinicians to understand overall oral health and diagnosis problems related to it.

Dentitions are divided into two stages in humans. The primary dentition has 20 teeth and the permanent dentition has 32 teeth. A numbering and encoding scheme is required because of age-related changes in tooth occurrence and positioning [16]. For charting and communication purposes, the Tooth Numbering System (TNS) assigns a unique number to each tooth. Different ways of labeling and encoding teeth have been employed in the past. Federation Dentaire International (FDI) and Universal Teeth numbering (UTN) are the most commonly used methods of tooth numbering systems. The ideal TNS, according to the FDI committee, is easy to learn and teach, easy to say in conversation and dictation, easily communicable in type, quickly translated into digital output, and easily adaptable to standard charts used in standard procedure as shown in Fig. 8 [17].

However, annotation of dental radiographs requires much human effort, and it is a very time-consuming process. Hence tooth segmentation has to be automatic, and this will be the first step towards developing the automatic dental care assistant model. Teeth identification and segmentation are must and the first part needed to develop a model. Many researchers have developed image processing algorithms to attain satisfactory accuracy for the segmentation and classification of dental radiographs. However, many of these algorithms perform image enhancement before image segmentation and feature extraction. Table 1 indicates the different researchers had used different deep learning algorithms for automatic teeth identification and numbering.

Article [29], introduced semi automatic method to identify human in forensic dentistry application where use of image processing and pattern recognition techniques had been proposed. This method involves three stages i.e. image segmentation, tooth feature extraction and tooth feature matching. Proposed method shows the tooth pixel and background pixel distribution in the image. A system based on content based archiving and retrieving dental radiographs for human identification is proposed in article [30]. There are three primary stages in it: dental picture categorization, bitewing image segmentation, and retrieval based on tooth shapes utilizing bidirectional Hausdorff distance. During retrieval, a post mortem (PM) bitewing image is segmented to recover teeth outlines, which are then utilized to search the antemortem (AM) database for the most similar images using the Hausdorff distance measure [30].

A new method for teeth restoration uses signature vectors obtained at key spots on the contours of the teeth to represent and match dental contours. Nomir and Mohamed [31] developed this teeth separation based on integral projection. The gap between the signature vectors of AM and PM teeth is used to calculate matching vector scores. Said [14], proposed a method to get desired region of interest (ROI) after analyzing the connected region. The mathematical morphological approach is used which combines one after another morphology filtering operations to get better segmentation results. Another experiment was performed by Lai and Lin [32] using texture based feature and fuzzy based region growing for segmentation but this method has limitation that it does give good result when no uniform exposure of the texture of gums is shown.

Image enhancement methods like holomorphic filtering and homogeneity based contrast stretching technique used for improving segmentation i.e. to separate teeth from background, in combination with teeth alignment, a simplified form of a sequence alignment algorithm is utilized. Simple version of a sequence alignment algorithm used for teeth alignment. This approach given by lin et al. [15] shows better classification accuracy on images with excessive dental work, significant teeth occlusion, and uneven illumination.

Label tree using cascade network structure approach given in article [33] can handle a wide range of challenging scenarios, such as tooth loss, decayed teeth, and crowned teeth, all of which are typical on X-rays taken from patients. Silva and oliveira [18] used mask recurrent convolutional neural network for automatic teeth segmentation with novel dataset.

For tooth classification and numbering, end-to-end neural networks were proposed in [22]. Authors had studied and analyzed four neural networks architectures namely mask region based convolutional neural network(Mask RCNN), path aggressive network (PANet), hybrid task cascade (HTC) and residual networks(ResNet). Observations are as follows: it is absolutely possible to detect, to segment and to number the teeth using above mentioned architectures, performance can be improved with correct selection of neural network, PANet give best result with 71.3 percentage on segmentation, 74 percentage on numbering. Fine tuned mask RCNN algorithm of deep learning to identify and locate the teeth on panoramic radiographs used in article [10] for automatic tooth segmentation.

Use of visual geometry group-16 (VGG-16) CNN along with heuristic algorithm attained good results in teeth detection module proposed in article [9]. Haghanifar and Majdabadi [21], proposed use of evolutionary algorithms to extract teeth automatically from the panoramic

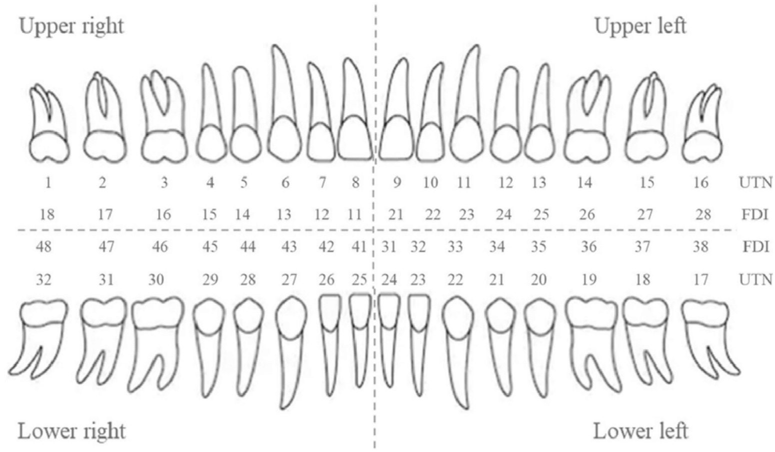

Fig. 8. FDI teeth numbering system: 11–18 = right upper 1–8, 21–28 = left upper 1–8, 31–38 = left lower 1–8, 41–48 = right lower 1–8; 1. Central incisor, 2. Lateral incisor, 3. Canine, 4. First premolar, 5. Second premolar, 6. First molar, 7. Second molar, 8. Third molar [17].

Table 1
Summary of different methods use for teeth identification and numbering.

Paper	Year	Method	Image type	Total images	Accuracy
[18]	2018	Mask RCNN	Panoramic radiographs	1500	0.928
[19]	2019	FCN architecture	Panoramic radiographs	1201	Disc score 0.934
[10]	2019	Mask R-CNN model	Panoramic radiographs	1024	F1 score 0.875
[9]	2019	CNN architecture	Panoramic radiographs	1352	Specificity 0.9994
[20]	2020	RCNN with optimization algorithm	Panoramic radiographs	900	F1 score 0.097
[21]	2020	Evolutionary algorithms	Panoramic radiographs	42 (total 1229 teeth)	77.56
[22]	2020	Mask R-CNN, PANet, HTC, and ResNeSt,	Panoramic radiographs	1224	0.90
[23]	2021	FCRNN	Panoramic radiographs	27	83.33
[24]	2022	CNN based on LeNet	Panoramic radiographs	300	95
[25]	2022	Faster RCNN	OPG images	591	F1 score 0.98
[26]	2023	Neutrosophic logic	Panoramic radiographs	2120	93.20
[27]	2023	Dual path transformer based network	Panoramic radiographs	1500	
[28]	2023	Unet	Panoramic radiographs	1500	98.53

radiographs. Further authors had separated upper and lower jaws, followed by use of genetic algorithm which is used to find the teeth valley gap. This technique is applied over 42 panoramic radiographs and achieves 81.14 percentage accuracy for upper jaw and 73.63 percentage for lower jaw.

Authors of [23], proposed the use of convolutional neural network (CNN) algorithm to detect and classify submerged molar teeth. Detection part involves faster region based convolutional neural network (faster RCCN) architecture which process the radiographs to detect the contour of submerged teeth. Performance of the system achieves accuracy level same as expert. Automatic tooth recognition from dental radiographs can be a useful tool for dentists during treatment. It would not only lighten the workload of dental practitioners, but it will also reduce interpretation errors and diagnostic time [20].

Any computer-assisted analysis system requires a fully automatic teeth isolation procedure as a pre-processing step. Research shows tooth isolation had been done in many different cases like severe tooth occlusion, extensive dental work, and uneven brightness. In dental radiography, segmentation is dividing a digital image into different portions (pixel set) or teeth to facilitate image processing and tooth identification. The goal of image segmentation is to distinguish teeth from other regions of the image. Researchers have proposed several segmentation methods, including region-based, boundary-based, threshold-based, cluster-based, and category-based.

Article [9], presented the novel method using CNN is used to detect and number the teeth automatically. Both teeth detection and numbering tasks were investigated using CNN-based architectures. The radiograph is processed by the teeth detection module, which determines the boundaries of each tooth. It is built on the cutting-edge faster R-CNN architecture. The teeth numbering module uses the FDI notation to classify discovered tooth pictures. It combines the traditional VGG-16 CNN with a heuristic approach to enhance results in accordance with the guidelines for tooth spatial layout. The whole architecture and workflow are depicted in the Fig. 9 [9]. The proposed method for teeth detection achieved sensitivity 0.9941 and precision 0.9945 as shown in Fig. 10 and method used for classification achieved sensitivity 0.9800 and specificity 0.9994 as shown in Fig. 11.

Different CNN architectures had been used to detect the teeth and further to number them. As per the research study, FCRN gives better results for the teeth detection stage. Further, VGGN 16, along with heuristic algorithms, gives a better result of tooth numbering [18]. Recently, researchers have applied different deep learning algorithms in which FCRNN is a commonly used architecture. Also, FCRNN combined different methodologies to improve the result. For example in article [20] used FCRNN and prior knowledge-based candidate optimization technique to improve results.

Furthermore, any of the examined designs can recognize, segment, and number teeth; with the exemplary neural network architecture, performance can be significantly improved. The PANet produced the best results of all [22]. In article [25] permanent teeth had been identified in 3 step process. Author had used UNet to identify ROI, faster RCNN to identify teeth from ROI, lastly VGG-16 to classify tooth in 32 category.

Authors of [26] used patch level feature, gradient feature, entropy feature, and local binary pattern to transfer the input dental radiography image into the neutrosophic domain. The use of neutrosophic logic aids in the localization of the first region of interest. Further authors have used a fuzzy c-means technique to segment a more accurate region of interest and achieved an accuracy of 93.20 percent.

A panoramic-segmentation based strategy that integrates the result of the instant segmentation with background semantic segmentation

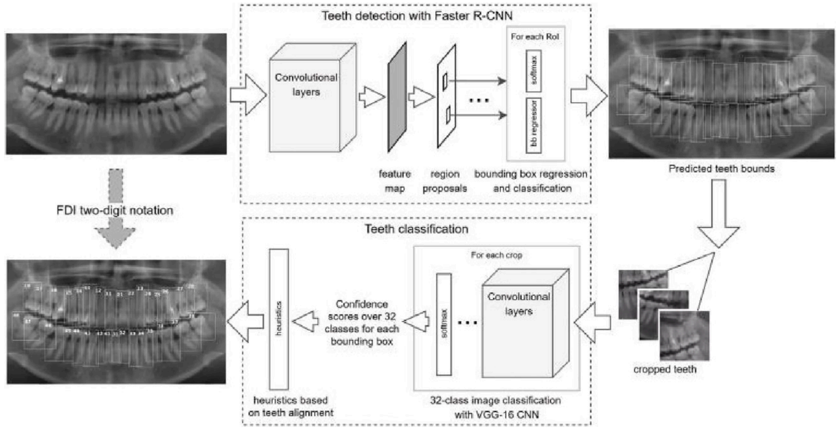

Fig. 9. Teeth detection and classification architecture as proposed in [9].

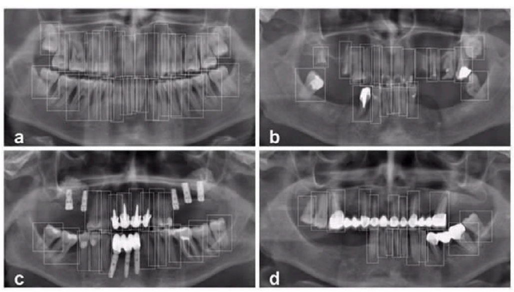

Fig. 10. Teeth detection result [9].

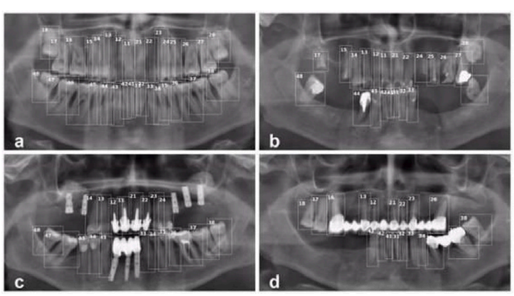

Fig. 11. Teeth numbering result [9].

proposed by Kanwal et al. in [27]. They have presented novel architecture for teeth segmentation that uses a dual path transformer based network combined with panoptic quality PQ loss function.used Unet to overcome problems faced in panoramic dental radiographs such as blurred interdental boundaries and low contrast between teeth and alveolar bone. To begin this approach authors have used a squeeze-excitation module in the encoder and decoder part of the UNet architecture followed by a multi-scale aggregation attention block incorporated to address the irregular shape of the teeth and low contrast issue. Finally, dialed a hybrid self-attention block to filter background region information which is not required for segmentation without boosting network parameters. The model obtains an accuracy of 98.53 percent. To conduct panoramic radiograph segmentation, Swin-Unet a transformer-based Ushaped encoder–decoder architecture with skip connections is introduced for panoramic radiograph segmentation in [34]. Authors of [35] introduced the pediatric dental radiograph dataset. Authors observed that Unet performed well among other deep learning architectures.

3. Dental disease detection

Due to the acquisition techniques and the minimal use of X-ray radiation, intra-oral dental radiographs frequently have poor image quality. Dental radiograph anomalies are difficult to detect because of the poor image quality caused by the low X-ray dosages employed. A misdiagnosis could result from poor image quality. Image processing techniques like contrast enhancement algorithms (CEA's) are widely used in dentistry to improve digital dental radiographs and aid dentists throughout the interpretation process [36].

Dental caries is one of the world's most frequent dental problems. It is the medical term for a typical dental cavity or tooth decay. Tooth decay or cavities are referred to as dental caries. Specific bacteria cause caries and these bacteria produce an acid that destroys the tooth enamel as well as the dentin layer [37]. It can develop in either the occlusal region, which contains pits and grooves in the back teeth, or the approximal region, which includes spaces between teeth or adjacent teeth [38].

This bacterium now transforms sugar and carbohydrates in meals into acids, which break down minerals in the enamel and harm the enamel's dentin layer as it passes through the pores. Finally, by dissolving these two layers, a cavity is created [38].

Caries are initially detected through visual inspection, but this is insufficient and not periodic because many discretionary parameters are involved, and the doctor's experience also plays a crucial role in this process. For the similar issue, doctor's opinions may differ, which directly impacts the treatment process. Hidden caries, caries between the tooth and depth of the caries are still challenging to identify [21] .

Dental radiographs must be analyzed to improve and quantify medical images for correct diagnosis. Due to minor lesions that are not visible to the human eye, cavity detection can be arduous. Image processing techniques aid in identifying caries, providing dentists with accurate results of carries affected area [44]. Dental caries is a preventable infection in and of itself, but it should be recognized as soon as possible before the tooth is destroyed. Dental caries, once developed, can be detrimental to the tooth and the surrounding region since they can infect the root and nerves, ending in the tooth's extraction [38].

In the literature, there are three types of dental caries; tooth decay begins with plaque. Enamel Caries, which damages the tooth on the surface or in between two teeth, is the second most prevalent. Pulpal Caries, which are comparable to root caries or root surface caries, is the third type [37]. Table 2 gives the summary of the techniques used for dental caries detection.

There are different models researchers had used for detection of different dental diseases as shown in Fig. 13. Authors of [51], initiated study to detect particular abnormalities related to teeth structure i.e. to detect periapical radiolucency (PA), widen periapical ligament space

Table 2
Summary of different methods used for caries detection.

Year	Author	Summary of work done
2013	[39]	A method for detecting occlusal caries on excised teeth is proposed that is automatic and unsupervised. 85.4 and 83.5 sensitivity and precision were achieved. By removing the false positives, it can be even better.
2015	[40]	They discovered that sharpening filters, which are distinct from other filters, yielded the highest ROC value.
2016	[37]	They used the pre-processing techniques bitewing radiographs after that edge detection techniques, thresholding and connecting component labeling. These connected components detects the caries.
2017	[41]	Presented bitewing type of a radiographs used to identify dental caries using deep fully convolutional neural network. This study had shown a precision of 0.615 and recall of 0.805.
2018	[42]	Utilized transfer learning for training data set of 3000 periapical radiographs and a pre-trained google net inception v3 CNN network for pre-processing it. Author had identified dental caries for three teeth, with accuracy of 89 (premolar), 88 (molar), 82 percentage (pre molar–molar).
2019	[43]	Proposed carries detection system which uses different techniques like laplacian filter for image sharpening, morphological operations and adaptive thresholding for segmentation and lastly support vector machine as classifier. The result values:sensitivity 1, specificity 0f of 0.8667 and precision of 96.08 percentage and accuracy of 96.88 percentage.
2020	[44]	Proposed a method for detection of tooth surface as normal or along with dental carries, back-propagation neural network used over 105 intra-oral digital radiographs. This gives accuracy of 0.971.
2020	[36]	Experiment performed on 10 patient's digital intraoral radiographs to detect dental caries using texture features maps. In this research for image analysis and transforming them, run length matrices (RLM), local binary pattern (LBP), k-means clustering (CLU), first order feature (FOF) techniques were used. Results shows that improvement in detection of carries achieved by CLU and FOF texture feature maps. Where as LBP and RLM shows less accuracy with blur edges.
2020	[45]	Proposed unified carries detection and assessment (UCDA) framework to detect carries on children's first molar tooth. During this work author's had also developed children's oral image database which comprises of 1368 primary school's children with standard diagnostic annotations.
2021	[46]	Used CNN model with a U-shaped deep CNN (U-Net) for caries identification on bitewing radiographs. Author has received following result precision 63.29 ; recall 65.02 and F1-score 64.14 percentage.
2021	[47]	Proposed a convolutional neural network to detect caries lesion mandibular and maxillary third molars. For detecting carious lesions of third molars on panoramic radiographs, the method had an accuracy of 0.87, a sensitivity of 0.87, a specificity of 0.86, and an area under the curve of 0.90.
2022	[48]	Used YOLO based CAA system for caries lesion detection with more than 90 percentage accuracy.
2023	[49]	Used YOLOv3 to detect caries at two different levels of intersection over union i.e. 0.5 and 0.75.

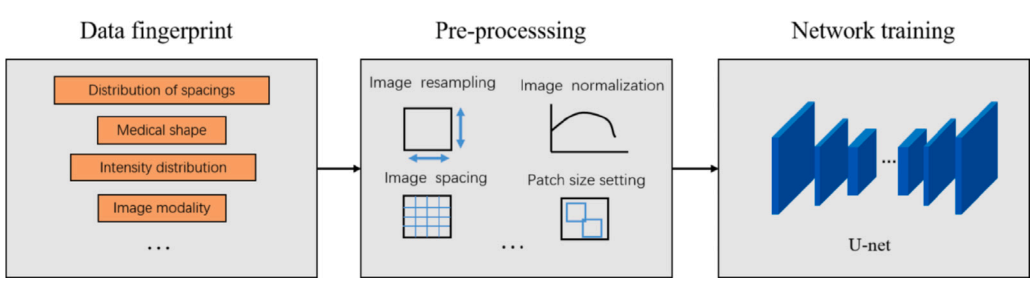

Fig. 12. Dental disease segmentation workflow as proposed in [50].

(widen PDLs) and loss of lamina dura (Loss of LD). In the experiment contrast enhancement algorithms like adaptive histogram equalization (AHE), contrast limited adaptive histogram equalization (CLAHE) and sharp contrast limited adaptive histogram equalization (SCLAHE) had used. Result shows use of CEA methods slightly improve the abnormalities detection particularly PDLs and loss of LD abnormalities. The increase in bacterial infection lead to diseases called periodontists or periodontal diseases. The main reason for this is poor oral hygiene. It can be detected through different techniques. Article [52] had used dental plaque as input to diagnosis periodontal disease. In this experiment tensorflow framework develop by google had been used. Total 1000 dental plaque images were captured and prepossessed using sharpening, resizing, brightness adjustment was done.

New approach, hybrid graph cut segmentation approached is developed in article [53]. The impacted regions are segmented in this method by drawing a scribble line on the image to forecast the various sections. Dental features are extracted using statistical method. Further dental disease are detected using deep learning with convolutional neural network which achieved accuracy up to 97.07 percentage. Comparative analysis on three different networks (AlexNet, VGG-16, and Detect-Net) is done in article [54]. Author concluded that Detect-Net highest efficiency in detection process. It gives precision, recall, F-measure detection in incisor region '1'. Hence it shows perfect detection.

To help dentist in diagnosis the dental disease problem, article [55] proposed a system where annotation is done manually to provide the input to the CNN architecture. Each tooth or group of teeth, as per available in radiograph are numbered and a report detailing the dental issues for each case is provided. It is important to detect dental cysts to have good oral hygiene. Symptoms related to cysts depends on the location and size. Infection in the tooth causes the dental cysts. It is important to detect cyst at early stage to avoid further complications related to teeth. Authors of [56], applied fuzzy membership function of each pixel and local spatial information of neighborhood pixel. This

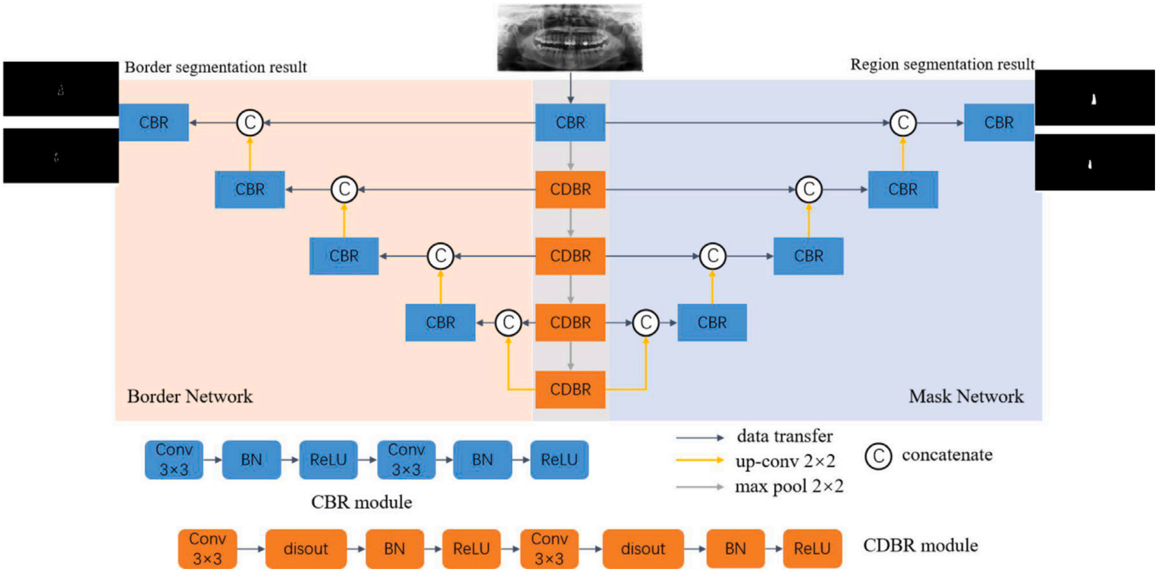

Fig. 13. BDU-Net structure for teeth instance segmentation as proposed in [50].

hybrid multiregional segmentation method give good results over traditional techniques of segmentation like histogram based segmentation to detect cyst.

Traditional method of bone density examination is complex and expensive. Recently dental panoramic radiographs had given cost effective solution to osteoporosis screening. In article [57] total 680 dental panoramic radiographs had used in the proposed method with different transfer learning technique on deep leaning models like basic convolutional model with three convolutional layers (CNN3) visual geometry group deep CNN model (VGG-16), transfer learning model from (VGG-16), (VGG-16TF) and fine tuning with the transfer learning model (VGG-16-TF-FT). According to the author, deep learning models are helpful and reliable in the computerized screening of osteoporosis patients. Article [58], developed deep learning model to detect apical lesions on panoramic radiographs. But authors claim that it did not show generalizability. Article [59] had identifies different dental problems where, CNN had taken in form of NASet which has different max pooling layers. Model achieves 96 percent accuracy. Author's of [60] used faster RCNN architecture for 17 different anomaly detection. Proposed model achieves 0.99 sensitivity.

In [61] authors have used a basic convolutional neural network for the dental radiographs classification under healthy and affected categories, which achieves an accuracy of 97.87 percent. For the first time, authors of [50] used two enhanced versions of the Unet: nnUnet and border guidance and feature map distortion (BDU-Unet) to construct an AI framework. In this by modifying the hyperparameters based on data properties, nnUNet can automatically adapt to any dataset. The semantics of dental diseases were segmented using nn-Uet, as one nn-Unet can only segment a single disease, four parallel nn-Unets were constructed to segment caries, impacted teeth, complete crowns and residual roots. The nn-Unet evaluates the features of the input dataset and executes an appropriate pre-processing operation on it. The nn-Unet's hyperparameters such as radiograph block size, training batch size, and downsampling timings were automatically set 12. BDU-Unet focuses on improved generalization capabilities and instance boundary adjustment. It was introduced to acquire tooth position information. It consists primarily of two distinct subnetworks i.e. subnetwork to generate the region segmentation, while segmentation borders are adjusted by border subnetwork as shown in Fig. 13. This framework shows great specificity in identifying impacted teeth, full crowns, missing teeth, cavities, and residual roots.

Author's of [62] emphasizes panoramic dental radiographs to diagnose accurate dental disease using deep learning techniques. The you only look once version 3 (YOLOv3) model was used by Panyarak et al. [49] to detect caries at two different levels of intersection over union i.e. 0.5 and 0.75. Authors conclude that YOLOv3 was able to identify and categorize carries but failed to predict caries in the outermost region of the enamel. Rajee et al. in [63] proposes a novel segmentation approach based on Curvilinear Semantic Deep Convolution (CSDCNN). Following segmentation, the suggested inception resnetv2 functions as a classification technique to determine caries in dental radiographs. The authors have considered four diseases for classification, which are periapical infection, dental caries, periodental, and pericoronal diseases. The model achieved 94.51 percentage of accuracy. Comparative analysis of Graphical Neural network (GNN) and CNN proposed for prediction of dental disease proposed by [64], in which GNN and CNN achieved accuracy 98 percent and 93 percent respectively. Table 3 list the different methods used for dental disease detection.

4. Applications

Deep learning algorithms have recently been incorporated into CAD, with promising results for various medical applications. Deep learning's qualitative and quantitative applications in dentistry are growing. However, specific areas need to be supplemented to ensure that deep learning research in oral and maxillofacial radiology continues to progress [71].

Dental science applications range from dental emergency to differential diagnosis of mouth pain, radiographic image interpretation, facial growth analysis in orthodontics, and planning the best prosthesis for a specific patient. In medical applications, computers may be able to provide clinical diagnostics and suggest therapies using deep learning [72]. DL has been used to diagnose and predict diseases and offer therapy suggestions due to its capacity to detect linkages and patterns in enormous amounts of data. In the discipline of dentistry, artificial intelligence and deep learning are used in a variety of ways [73]. Table 4 summarizes all the dentistry application using deep learning.

The latest generation of human-safe robots can now interact directly with human co-workers, assisting them and relieving them of mundane and time-consuming chores. Simultaneously, they demonstrate a high level of competence and are becoming more economically relevant [74]. Dentistry is a promising field since it offers multiple chances for assisted work and automation of simple routine chores, allowing dental professionals to perform more efficiently while also

Table 3
Summary of different methods used for dental disease detection.

Paper	Year	Disease type	Method	Data set	Total images	Radiograph type	Accuracy (percentage)
[39]	2013	Occlusal carries	CEAs	Author's data set	60	Photo images	92.3
[65]	2017	Dental caries	CNN and transfer learning	Author's dataset	80	RVG	87.5
[65]	2017	Periapical infection	CNN and transfer learning	Author's dataset	110	Radio visiography	90.0
[66]	2019	Root caries	SVM, K nearest neighbors	NHANES dataset	5135	Questionnaire data set	SVM: 97.1, KNN: 83.2
[67]	2019	Occlusal caries	Mask RCNN with transfer learning	Paediatric dentistry NKUA	88	photo in vivo with an intraoral	88.9
[53]	2019	Oral cavity	Hybrid graph-cut technique and CNN	Author's data	1500	Dental Xrays	97.07
[43]	2019	Dental caries	Textural feature	SJM dental	64	Digital Xrays	96.88
[45]	2020	Caries	UCDA frame work	Child-OID'	1368	Oral images	95.25
[44]	2020	Dental caries	Back propagation neural network	SJM Dental College	105	Intraoral radiographs	97.1
[21]	2020	Dental caries	Ensemble transfer learning and capsule classifier	Diagnostic Imaging Center	470	Panoramic radiographs	86.05
[68]	2020	Oral cancer	Deep neural network method	MeMoSA	2155	Dental images	F1: 87.07
[57]	2020	Osteoporosis	Transfer learning and fine tuning with a deep CNN	Korea university hospital	680	Panoramic radiographs	84
[55]	2020	Restorations	Semantic segmentation CNN	Author's data set	2000	Panoramic	89
[69]	2021	Tooth decay, periapical,	RCNN	Author's dataset	2900	Periapical radiographs	Precision: 0.5 recall: 0.6
[70]	2021	Periodontal bone loss	Two-dimensional Otsu (2D Otsu) threshold segmentation	Author's dataset	350	Panoramic radiographic images	92.8
[60]	2022	17 fine-grained anomalies	Faster RCNN	Author's dataset	23 000	Panoramic radiographic images	Sensitivity 0.99
[64]	2023	Dental diseases	GNN and CNN	Author's dataset	–	Panoramic radiographic images	98, 93

improving the quality of their work and care [74]. Many applications using robots had been observed in dentistry, such as Maxillofacial surgery, computer-assisted implant surgery, root canal treatment and dental plaque removal, and robotic arms for tooth preparation [75].

Forensic dentistry applies dental expertise to criminal and civil laws implemented by police agencies in a criminal justice system. Investigators use forensic dentists to help them identify people who have been found. In dental bio-metrics, dental radiographs are used to identify humans. The dental radiograph provides information such as tooth shapes, adjoining teeth' relative placements, and the shape of the dental treatment (e.g., crowns, fillings, and bridges) [76].

Other forensic dentistry applications involve assessing bite marks injuries, age estimation, and assessment of mass fatalities. Further sensitivity of detecting caries and prediction of oral treatment need in children is done with the help of deep learning algorithms. Furthermore deep learning has been promoted as a technique for improving pathogenesis, diagnosis, the development of new risk-assessment methodologies, the prediction of periodontal disease and bisphosphonate-related osteonecrosis of the jaw, and esthetic and cosmetic dentistry treatment planning [77].

Clinical decision support system (CDSS) can be utilized in different specialization areas of dentistry; for example, in orthodontics, tooth extraction decisions are formulated computationally for forecasting the sizes of uninterrupted canines and premolars. In periodontology, periodontal disease diagnosis utilizes several classification algorithms is a preliminary study; CDSS is used in dental surgery to predict dental treatment and dental implantology [77]. Digital Smile Design (DSD), 3Shape software (3Shape Design Studio and 3Shape Implant Studio), Exocad, and Bellus 3D are examples of digital dentistry utilized by dental practitioners [78]. Vijayakumari et al. [79] proposed 3 stages network for gender classification. It includes pre-processing, gradient-based recursive threshold (GBRT) segmentation, and finally Resnet50 classifier. This proposed model achieved 0.99 sensitivity.

5. Dental treatment prediction

Uncertainty, imprecision, and vagueness are all characteristics of medical knowledge. Choosing a treatment strategy might be challenging. The dentist's intelligence, intuition, education, experience and skills are all required. When multiple dentists provide treatment plans, all of these factors lead to levels of variance in treatment plans [95].

Because it is often based on the practitioner's experiences, orthodontic treatment is crucial and complex. A poor decision could lead to a slew of issues during dental treatment. It is possible that unfavorable outcomes will occur or the therapy will not be completed in the worst-case scenario [96]. Failure of anchoring control, the irregular inclination of the anterior teeth, undesirable profile, inappropriate occlusion, insufficient overjet and overbite, and difficulty closing extraction spaces are all possible issues.

Most dentists make decisions based on their experience and knowledge, using information from clinical examinations, pictures, dental models, and radiographs. In many circumstances, the decision is based on the practitioner's heuristics because there is no formula for the treatment plan. This frequently results in intraclinician and interclinician variation in treatment planning. Furthermore, the treatment strategy may alter depending on the records utilized for the diagnosis [97]. Furthermore, treatment planning disparities between skilled and less-experienced practitioners can emerge. Many papers on artificial intelligence and bioinformatics for dental treatment prediction, have recently been published. Deep learning with a neural network system is one method, using which automatic dental treatment predictions model to supports clinicians decisions had been developed [98].

Xie et al. [99] proposed treatment prediction technique for orthodontic treatment to decide whether tooth extraction is needed by using artificial neural networks (ANN). The artificial neural network used in this study was successful in detecting whether extraction or

Table 4
Summary of different dental applications.

Paper	Year	Application	Method	Total images	Radiograph type	Accuracy (percentage)
[80]	2012	Human identification	SVM	16	Dental radiographs	91.6
[81]	2012	Human identification	Contour based	93	Bitewing radiographs	94.3
[82]	2013	Human identification	Generation of dental code	30	Panoramic radiographs	90
[83]	2013	Human age detection	Kvaal's method	150	Panoramic radiographs	Error=1.39
[84]	2014	Human identification	Shape registration Method	55	Ortho Pantomo Graph (OPG)	72
[85]	2015	Human age detection	Segmentation	70	Periapical radiographs	Error=0.04
[86]	2016	Human identification	Morphological skeleton transform, SIFT	10	Dental radiographs	94
[87]	2017	Human age detection	Transfer learning ,CNN	400	Panoramic radiographs	51
[88]	2018	Human age and gender identification	Emre Avuçlu et al algorithm	1313	Panoramic dental radiographs	99
[89]	2019	Human age and gender identification	Backpropagation algorithm	162	Panoramic X-ray	99.9
[90]	2020	Human identification	Deep convolution neural networks	1168	Dental radiographs	87.21
[91]	2020	Human identification	CNN	15 868	Panoramic radiographs	85.16
[92]	2020	Human identification	Speeded Up Robust Features (SURF)	61 545	Panoramic radiographs	100 for 43 test cases
[93]	2020	Human identification	Transfer learning using AlexNet	1585	Panoramic radiographs	95.5
[76]	2020	Human identification	Dual Cross Pattern and (k-NN)	300	Dental panoramic radiographs	88
[94]	2022	Gender classification	CNN	–	Dental panoramic radiographs	95
[79]	2023	Gender classification	Resnet50	285	Dental panoramic radiographs	94

nonextraction treatment was better for malocclusion patients aged 11 to 15 years old, with an accuracy of 80 percentage. For broken teeth treatment suggestion model developed in article [95]. Author used a fuzzy inference mechanism-based decision-making system to decide the possible treatments. The accuracy of the suggested decision support system for the treatment of damaged teeth boosts dentist's confidence while making treatment decisions.

An artificial intelligence expert system that uses neural network deep learning to diagnose extractions of the tooth and evaluate the model's performance deigned in article [96]. This approach uses a back-propagation approach, four neural network deep learning models for extraction diagnosis were created and tested. The models had a 93 percent success rate in treatment prediction of extraction vs. nonextraction and 84 percent success rate in diagnosing extraction patterns in detail. For orthodontic treatment morphological assessment of facial features automatically obtained using deep learning model by authors of [100]. The proposed method resulted in 64.8 percent accuracy.

Yang et al. [101] presented an automated root canal dental work prediction quality assessment approach based on dental radiograph categorization, which combines medical specialist's knowledge with image processing algorithms and convolutional neural network-based learning. F1 score improved, when the root apical region is used instead of the complete tooth. Another approach to predict requirement of orthodontic treatment developed in [102] to assist general practitioners. As the underlying model for determining the need for orthodontic therapy, a Bayesian network (BN) was used. The approach produced encouraging results, with high accuracy in predicting patients into groups that required or did not require orthodontic treatment.

A new artificial intelligent model for deciding whether or not to have dental surgery and determining how much to extract proposed in article [103]. The model's success rate was 96 percent for surgery/nonsurgery prediction diagnosis and 91 percent for comprehensive diagnostic of surgery type and extraction decision diagnosis. The deep learning algorithm was created using an artificial neural network that can assist in predicting the complexity level of a endodontic treatment and deciding whether or not to refer it in article [97]. The study adds automation to the traditional approach of forecasting a case's complexity level, allowing for faster decision-making and, if necessary referrals, with a sensitivity of 94.96 percentage.

Fluoride, fillings, and root canal treatments are the three types of treatments predicted by the method proposed in article [104]. With the help of a deep convolutional neural network on dental radiographs, it detects tooth deterioration from dental X-ray images and predicts the required treatment. The model's total accuracy is 87 percent. The fluoride treatment had the best prediction rate of 98 percent and root canal detection with an 88 percent rate. With a rate of 77 percentage, the filling procedure resulted in decreased classification accuracy. In article [105] author had used a tiling approach to increase the accuracy of multi-label segmentation of dental restorations on panoramic radiographs which had given promising results in predicting root-canal, crowns, implants. Authors of [106] recommended approach comprises various deep learning-based strategies for dental and bone problems and treatments. The innovative incremental learning architecture suggested by the author will allow for gradual and improved comprehension of dental illness as well as the transfer of this knowledge to an AI-based model via active interaction among the toolbox and the practitioners.

It is inevitable that humans must take the lead in the execution of dental surgery, diagnosis, and treatment planning. When a physician makes a judgment, an artificial intelligence techniques may be used as an auxiliary reference, especially in uncertain cases to predict the suitable dental treatment. The employment of artificial intelligence model as a support tool for treatment planning can be beneficial.

6. Dental radiographs data set

In medical imaging, artificial intelligence continues to pique people's curiosity. Several applications cover the entire medical imaging life cycle, from image creation to diagnosis prediction. One of the main challenges to AI algorithm development and clinical use is the lack of sufficiently large, selected, and representative training data with expert labeling (e.g., annotations) [58]. To train, validate, and test algorithms, current supervised AI systems necessitate a data curation procedure. Most research organizations and businesses now have restrictions on data access due to tiny sizes of the samples, from small geographic locations. Furthermore, data preparation is a time-consuming and expensive procedure, resulting in algorithms with limited value and poor generalization. Medical image annotation necessitates a high level of clinical knowledge. Deep learning based approaches with supervised learning produces accurate results for medical image segmentation. However significant labeled datasets are required for this, and collecting them is time consuming operation requiring clinical competence [107]. With the introduction of deep learning models and large-scale annotated picture datasets, rapid and considerable improvement has been demonstrated in several computer-aided detection/diagnosis (CADe/CADx) systems.

Only a few sets of radiographs were accessible for dental image analysis until recently, and practically all of them were intraoral X-rays (bitewing or periapical). Article [18] released the UFBA-UESC dental radiographs data collection to fill this void, which has proven to be a community's most important resource. There are 1500 high-variability panoramic images in the data collection, which are classified

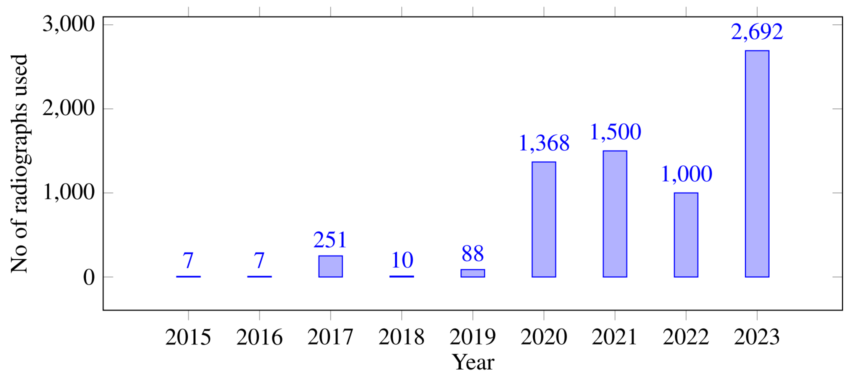

Fig. 14. Increase in the no of radiographs in data set over the years in teeth identification and numbering.

into ten categories. First data set was released in article [17], with only semantic segmentation annotations, which uses binary masks to distinguish teeth from background pixels by pixel. Later, article [108] updated the UFBAUESC dental images data set to add instance segmentation details, using 276 images with 32 teeth for training and validation and 1224 images for testing. UFBA-UESC dental images was the name of this data set. Due to the lack of an image database, yu et al. [45] proposed a new children's oral image database, Child-OID, which contains 368 primary school children's mouth images with standard diagnostic annotations and labels, to test the performance of the unified caries detection and assessment (UCDA) approach. Recently the Tufts Dental Database (TDD) has been offered as a complete new dataset with the potential to revolutionize dental AI practise. A tooth segmentation mask, abnormality mask, maxillomandibular region of interest mask, eye-tracking gaze map, and written description of the anomaly are all included in TDD [109]. Authors of [35] published a pediatric dentistry dataset for caries segmentation and dental disease detection. Authors have created a segmentation dataset appropriate for deep learning using their three internationally published adult dataset, totaling 2692 dental radiographs.

It was not easy to compare the studies objectively because the whole data set used in the study was created in-house. In the medical field, efforts are required to develop algorithms that can be employed in medical applications. To do so, researchers must offer anonymized data from their studies, as well as legal and institutional permission from each jurisdiction. A shared, open repository that can continuously acquire, classify, and retain freely available data is also needed in the dentistry business. It is also crucial to understand the importance of data uniformity and data set development standardization in dentistry. Because of the nature of dental radiographs, it is anticipated that hybrid data sets from many machines and environments will be necessary to achieve clinically meaningful high accuracy. As a result, in order to employ deep learning in medical practice, it is important to highlight the need to build a large-scale dentistry public dataset [14]. For dental radiography, there is presently no international norm in place. Another challenge researchers face is a poorly labeled dataset. It can reduce model performance and introduce bias, lowering prediction accuracy [110]. Also, overfitting and poor generalization of new data can result. This low-quality data can be an inefficient use of resources, promoting prejudices and strengthening assumptions. Fig. 14 shows how the increased in the number of dental radiographs in data set over the year in teeth identification and numbering.

7. Discussion

This review indicates the significant advancements that have led to the current state-of-the-art in this field of dentistry. It gives a thorough and comprehensive evaluation of the literature on coronary dentistry based on 100 carefully chosen publications. Much contemporary medical research has centered on building artificial intelligence for diagnostic and therapeutic purposes [1]. Artificial intelligence is currently being used in the medical domain [74]. Watson, for example, has been utilized by doctors to help them make therapeutic diagnoses [71]. Because dental radiography is difficult to standardize, the clinical accuracy of AI in the dentistry profession must be evaluated using various cases and imaging modalities before AI can play a more significant role in diagnostic decision-making. In addition, current AI systems are black boxes, making it challenging for humans to recognize or change diagnostic criteria [1].

The varied range of imaging techniques and equipment used in dental practices is one of the limits of AI systems in dentistry. Various types of X-ray machines, sensors, and imaging techniques may be used in different dental clinics. Hence AI systems might find difficult to standardize and adjust to these differences can impair their analysis accuracy. AI systems rely on enormous and diverse datasets for training. There may be constraints in availability and well labeled datasets for various dental imaging modalities. This also makes difficult AI system difficult to provide accurate analysis. Diagnosing dental diseases frequently necessitates taking into account several circumstances, such as the patient's medical history, clinical symptoms, and radiographic results. This complicated context-dependent information may be difficult for AI systems to include in their diagnostic criteria. In addition to this Dentists rely on their clinical judgment which includes not just objective information but also their intuition and past experience. AI systems lack this human judgment, leading to misinterpretation.

As a conclusion, a visualization and customization tool for deep learning networks that humans can easily interpret and alter is necessary to improve AI's reliability. Machine learning algorithms have reformed traditional clinical elements used in the field of dentistry research. To satisfy the growing demand and for efficiency machine learning-based clinical decision support system (CDSS) was created to update the diagnosis and data management system. ML algorithms are crucial in the identification of dental disease and also serve as a link between the patients and the dentist via mobile-based applications. Yet the quality of current studies was still very low in terms of data collecting, study design, data preprocessing, model validation, and clinical applicability 111.

Because typical deep learning algorithms are limited in their ability to interpret raw natural data, feature extractors must be carefully designed in order to convert raw data into a format appropriate for recognizing or categorizing input patterns. The emergence of deep learning algorithms effectively overcame this constraint. Deep learning approaches are learning-based representations that enables a deep to be handed raw data and then process it in layers to construct appropriate representations for automatically identifying or categorizing input data [72]. The main advantage of deep learning is that these layers of features are learned directly from raw data using an overall learning method, rather than being built by human engineers and depending entirely on dentist's trained eyes. Computational technologies have been offered as decision-supporting tools to help specialists make a better diagnosis. Also, these deep learning algorithms have shown promising results in detecting oral cancer like diseases successfully using computer aided cancer detection and medical images [112].

Manual radiographs analysis becomes very difficult because of arbitrary teeth variation and no clear boundaries between tooth and bone due to uneven exposure and intensities. Due to a lack of suitable automated resources to assist in the interpretation of dental X-ray pictures, the assessment of these images is done empirically, that is, by relying solely on the dentist's experience [113]. Even though dentists are well trained to interpret radiographs, some factors like angulation, magnification, and variation, in contrast, may be ended with faulty diagnosis.

Many studies utilize manually pre-processed images to train architectures. A few papers also used a portion of the images to train architectures, resulting in architectures that do not learn whole images but networks that learned by dividing images into parts of a specified size. This technique, however, has limits because the network can only learn a small portion of the image rather than the complete image. Several articles used down-sampling, which may have resulted in the loss of essential image data. As indicated in several articles, these decisions appear to have been made owing to data or computational power constraints.

The ability of CNNs to recognize and identify anatomical features has shown promises, some have been taught to recognize and classify teeth from periapical radiographs [72]. In recognizing and identifying teeth, CNNs achieved a precision rate of 95.8–99.45 percent, closely matching the performance of clinical specialists, who had a precision rate of 99.98 percent [2]. Until specific post-processing processes were employed, the precision and recall of the classification work that gave each identified tooth an FDI number were unsatisfactory. Because of the disparity in pixel intensity between bone and tooth structure on radiographs, precise segmentation is difficult to obtain. The main problem is that radiographs show protruded teeth structure, nasal area, skeleton structure, and surrounding bone area. Also, the shape, size, and structure of teeth differ from person to person. For automatic tooth numbering and identification process, the root of the tooth in bone has no clear boundary similar to the crown of the tooth, which can be identified easily; hence segmentation of multi-rooted teeth is challenging [71]. Deep learning models cannot identify teeth numbers correctly in several complex cases, including missing teeth, filled teeth, teeth with premolar extracted, embedded teeth, teeth with bridges, and crowns [17].

Object detection networks do not learn the rule mentioned by FDI for teeth numbering in dental radiographs with high accuracy; as a result, teeth with the same category and similarity, neighboring teeth are wrongly classified. The accuracy of annotation and labeling of the data set used during training significantly impacts the prediction system's quality. Hence poorly labeled data lead to poor results [17].

Systemic diseases such as osteoporosis, carotid artery calcification, oral cancer have been suggested for screening using clinical assistance diagnosis (CAD) systems based on radiographs. Most past study approaches, are only valid when images characteristics are successfully recovered utilizing complex and manual image pre-processing algorithms or processes. If a radiograph is taken from a foreign environment or random noise is introduced, the prediction can readily be changed. This issue can be solved using the neural network approach [58].

Dental treatment failures can be caused by various causes that are difficult to predict before beginning the dental treatment, even for the most experienced dentists, and are sometimes inevitable. Once clinicians have completed the primary diagnosis, the application of deep learning provides various advantages in predicting and planning dental treatments. It provides an expert dentist's perspective on the difficulty level of a case's assessment and referral, especially for inexperienced or beginner dentists [97]. Each algorithm proposed in the reviewed literature has been evaluated by individual authors, either objectively (by the implementation of an objective image quality measure) or subjectively (by visual inspection); hence there is a gap in the generalizability of the data set as well as in results achieved.

collaboration between dental professionals and specialists can aid in the development of robust CAD systems. We propose a mandatory subjective analysis of the deep learning models's output in dental radiograph analysis is essential in addressing clinical viability and prospective improvements. The subjective analysis satisfaction index will indicate that the deep learning model correctly distinguishes the diseases, anomalies, and segmentation of teeth. It is also suggested that a clinical validation study to be conducted in which the deep learning model;s output is employed in real clinical situations. Deep learning models may require continual monitoring and retraining to adapt to changing clinical circumstances, according to discussions with specialists.

The use of AI in dentistry leads to various ethical issues, which include the risk of dehumanizing patient care, loss of personal touch, and possibly infringement on patient's consent. AI systems may fail to take into consideration a patient's specific beliefs resulting in confidentiality and ethical issues. AI systems can be biased by the data on which they are taught, thus leading to discrepancies in diagnosis and treatment. Excessive AI may also limit practitioner's ability to develop clinical skills and decision-making abilities.

As a result of this new knowledge, present diagnostic rules can be improved, and systems using deep learning can increase their performance over time. This paper states that in order to develop further and improve CAD, a well-coordinated effort between researchers and experts in these domains is essential. Virtual hospitals will assist in establish a remote healthcare system in future, owing to an effective computer architecture that applies deep learning models to image processing [114]. Finally, this survey assists in identifying areas where significant new contributions can be made.

8. Conclusion

This review offers a comprehensive look at the work that has been done in the field of dentistry using deep learning. Deep learning techniques have broad scope in different applications of dentistry that had been observed in the literature review of dentistry. The deep learning techniques are integrated with computer-assisted diagnosis (CAD) in many applications of dentistry, still few areas need attention. For example, annotation of images, feature extraction is still done manually, which is time-consuming. However, algorithms under development may have the potential to work from partially annotated data and effectively annotate images automatically and intelligently. Even if data is collected extensively and labor-intensive data annotation is performed precisely, there may be an inherent class imbalance within the data itself. Recent advancements in the literature suggest that there are algorithmic approaches to successfully such challenges. Future work could involve expanding on existing data generation methods like generative adversarial networks (GANs) to generate more diverse datasets without the need to collect and label/annotate individual samples. Another avenue in the future to examine is deep learning (DL) based approaches that are capable of learning from smaller datasets. Also, detection of caries, anomalies, and diseases at an early stage is challenging. Researchers may work on this aspect. The automated dental radiographs analysis will assist the dentist in improving their daily workflow. Finally, we have identified several unresolved challenges and future directions for this field's development.

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This article does not contain any studies with human participants or animals performed by the authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Informed Consent

Informed consent was obtained from all individual participants included in the study.

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