Report on Detection of Dental Caries from Dental X-rays

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Abstract :

Dental caries is an infectious bacterial disease affecting hard surface of the teeth and remains the most prevalent chronic disease world-wide that affects most of the population. Although it is preventable, it causes a major tooth loss. The primary step is to detect dental caries in the early stage itself using diagnostic imaging techniques. The digital dental *x*-ray is the commonly used method to detect and diagnose dental caries. The segmentation of dental *x*-ray images could be difficult due to the shape and intensity variation within the same dental *x*-ray images and from one image to another. This makes a challenging process to segment the dental *x*-ray images for diagnosis of caries. In this paper, a survey has been presented on segmenting the digital dental *x*- ray images for diagnosis of caries.

The tooth is a hard and mineralized anatomical structure responsible for cutting, crushing, and grinding food, consisting of three different parts enamel, dentin, and dental pulp. Dental caries is a disease caused by the activity of bacteria that metabolize sugar-producing acids that can destroy dental tissues The progression of caries can cause pain, sensitivity, and even tooth loss .Caries is the most predominant oral disease in the world, affecting approximately 2 billion people worldwide

Keywords: *Dental caries, dental X-rays, segmentation, diagnosis.*

1. INTRODUCTION

The deterioration of enamel and dentin caused by bacteria in dental plaque is a disease known as dental caries, which impacts oral health. In the absence of treatment, the disease can progress to the inner part of the tooth, known as the dental pulp, where nerves and blood vessels are present, causing inflammation and tooth loss [1]. Researchers have been developing computational methods for diagnosing various dental abnormal conditions, such as periodontal disease, dental abscess, and lesions in dental canals, by using different imaging modalities.

Dental Caries is also known as tooth decay or dental decay, which falls out on any tooth surface especially when there is continuous deposition of dental plaque. Plaque is an example of a bio film, which means it is not a disorganized collection of bacteria but a group of metabolically active microorganisms attached to a surface. So, it is important to detect caries using diagnostic devices. There are several devices commercially available for detecting caries such as Electronic Caries Monitor (ECM), X-rays, and ultrasound techniques. Among those, the most common method for detecting caries is X-rays, since X-rays are easy to access and cheaper when compared to other techniques. X-rays are commonly used in the field of dentistry for diagnostic purposes .defined as a disease of the hard tissues of the teeth caused by the action of microorganisms found in plaque on fermentable carbohydrates (principally sugars). Therefore, the detection of dental caries in a preliminary stage is an important task. This chapter has two major purposes, firstly to announce the availability of a new data set of panoramic dental X-ray images. This data set contains 1392 images with varying types of noise, usually inherent to this kind of images. Secondly, we present a complete case study for the detection of dental caries in panoramic dental X-ray images

Need of this study:

The aim of this study was to evaluate the efficacy of detecting dental caries under fixed dental prostheses (FDPs) through the analysis of panoramic radiographs utilizing convolutional neural network (CNN) based You Only Look Once (YOLO) models. Deep learning algorithms can analyze datasets of dental images, such as panoramic radiographs to accurately identify and classify carious lesions. Using artificial intelligence, specifically deep learning methods, may help practitioners to detect and diagnose caries using radiograph images.

Caries diagnosis has been addressed in previous systematic reviews (SRs), with a focus on methods using deep learning techniques and different types of radiographic modalities. In the goal was to identify different approaches for diagnosing caries in periapical images. In contrast, some studies only focused on investigating deep learning methods. Additionally, the systematic review presented in identified studies that employed machine learning algorithms but did not address the differentiation of exam acquisition for caries diagnosis. However, none of the previous studies has comprehensively addressed the comparison between different radiographic modalities, incorporating a variety of diagnostic objectives for dental caries, including the comparison of classical machine learning, image processing, and deep learning.

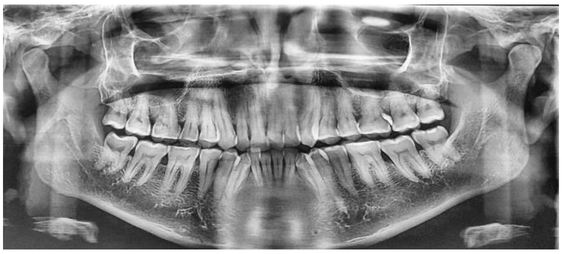
As a result, this study provides a comprehensive view of current advances and challenges in applying computational methods for caries diagnosis in X-ray images.

This review intends to establish a solid basis for future studies and research to improve the accuracy and effectiveness of caries diagnosis through radiographic images.

Dental X-rays

Dental X-rays or radiographs play a vital role in the diagnosis of dental diseases, such as cavities. Dentists often use radiographs especially in finding hidden dental structure, bone loss, malignant or benign masses and cavities that cannot be examined during visual examination [7]. Dental X-rays are purely essential, preventative and diagnostic tool that provide valuable information. Radiographic interpretation of dental caries should always be undertaken with a clinical examination of the oral cavity. Caries can be detected radio graphically only in the advanced stages when there is sufficient decalcification of tooth structures.



Apart from the various types of above X-rays, digital radiograph is one of the newest x-ray techniques. It is a form of x-ray imaging where digital x-ray sensors are used rather than traditional photographic fi lm. Digital radiography utilizes digital image capture device instead of x-ray film which gives advantages of quick image preview and applied to special image processing techniques which will enhance the overall display throughout the image. Digital radiography offers improved imaging through lower dose and lack of chemical processing and provided the possible to increase the diagnostic yield of dental radiographs. When compared to the dental x-ray films, digital dental radiographs are the most common method used for diagnosis of caries and widely used in clinical practice.

Dental Structures, Caries, and Imaging Modalities:

The tooth is a hard and mineralized anatomical structure responsible for cutting, crushing, and grinding food, consisting of three different parts: enamel, dentin, and dental pulp. Dental caries is a disease caused by the activity of bacteria that metabolize sugar-producing acids that can destroy dental tissues. The progression of caries can cause pain, sensitivity, and even tooth loss. Caries is the most predominant oral disease in the world, affecting approximately 2 billion people worldwide. Three main strategies are used to diagnose dental caries . The first technique is visual diagnosis, where the dentist examines the teeth with a mirror in the areas affected by caries. The second technique is laser technology, which allows early detection of cavities, even before they become visible. Finally, the third technique is the use of X-ray exams to acquire radiographic images to identify regions injured by dental caries. The four radiographic methods used for diagnosing dental caries are provided in this review:

- **Periapical radiographs** provide an expanded field of view that encompasses the root and crown of the entire tooth, in addition to the surrounding bone and periodontal tissues .
- **Interproximal radiographs or bitewing** provide a two-dimensional image that allows the visualization of the crowns of two or three adjacent teeth, facilitating the evaluation of the presence of caries between teeth .
- **Panoramic X-ray** offers a broad view of the dental arch, including the maxillary and mandibular bones, paranasal sinuses, and temporomandibular joints .
- **Cone beam computed tomography (CBCT)** provides detailed three-dimensional (3D) images of the teeth, bones, and soft tissues of the head,

allowing the dentist to visualize the presence of caries and other purposes, such as dental canal, low bone formation, and surgical treatment planning.

Statistics:

The aim of this systematic review was to provide an update on caries prevalence in older adults aged 60 years or above around the globe. Two independent reviewers performed a systematic literature search of English publications from January 2016 to December 2020 using Pubmed, Scopus, Embase/Ovid and Web of Science. The MeSH terms used were "dental caries", "root caries", "DMF index", "aged" and "aged 80 and over". Further searches in Google Scholar retrieved eight additional publications. The epidemiological surveys reporting the prevalence of dental caries or root caries or caries experience using DMFT (decayed, missing and filled teeth) and DFR (decayed and filled root) in older adults aged 60 years or above were included. Quality of the publications was assessed using the JBI Critical Appraisal Checklist for Studies Reporting Prevalence Data. Among the 5271 identified publications, 39 articles of moderate or good quality were included. Twenty studies were conducted in Asia (China, India, Vietnam, Singapore and Turkey), ten in Europe (Ireland, Norway, Finland, Germany, Portugal, Poland, Romania and Kosovo), three in North America (USA and Mexico), one in South America (Brazil), two in Oceania (Australia) and three in Africa (Malawi, Egypt and South Africa). The prevalence of dental caries ranged from 25% (Australia) to 99% (South Africa), while the prevalence of root caries ranged from 8% (Finland) to 74% (Brazil) in community dwellers. The situation was even worse in institutionalised older adults of which the mean DMFT score varied from 6.9 (Malawi) to 29.7 (South Africa). Based on the included studies published in the last 5 years, caries is still prevalent in older adults worldwide and their prevalence varies across countries.

(a) Study design: Epidemiological surveys investigating the prevalence of dental caries or root caries; and baseline findings from longitudinal studies. For multiple publications reporting findings from the same cohort, only the one with the largest sample size was included. Other types of studies such as case reports, literature reviews, letter, commentaries, case–control studies or studies analysing secondary data were excluded.

(b) Participants: older adults aged 60 or above;

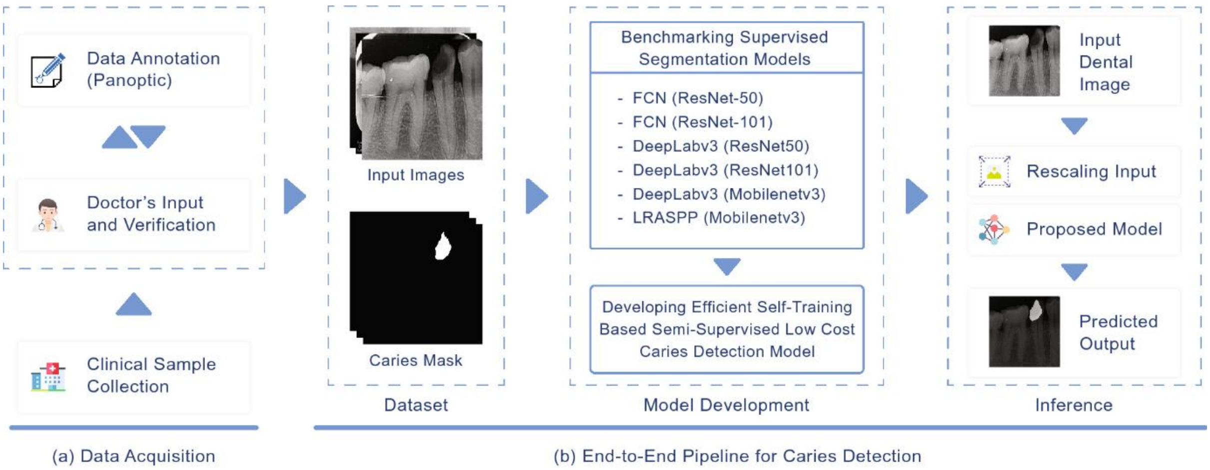
(c) Outcomes: dental or root caries prevalence or experience using DMFT (decayed, missing and filled teeth) and DFR (decayed and filled root).

Location	Median of Untreated Caries Prevalence	Median of Root Caries Prevalence
Global (20 countries, 39 studies)	49%	46%
Asia (5 countries, 20 studies)	66%	46%
Europe (8 countries, 10 studies)	46%	35%
North America (2 countries, 3 studies)	25%	95.3%

Location	Median of Untreated Caries Prevalence	Median of Root Caries Prevalence
South America (1 country, 1 study)	-	74%
Oceania (1 country, 2 studies)	25%	18%
Africa (3 countries, 3 studies)	49%	-

Methodology

In this section, we present our proposed methodology for caries detection in dental radiographs, which is mainly illustrated in Figure.



We will start this section by first describing the data collection process and formally formulating the problem. The data collection process involves two main steps (as depicted in Fig. 1), i.e., clinical sample collection and panoptic annotation and verification by an expert dentist.

Data collection strategy:
The data collection process involves two main steps clinical sample collection and panoptic annotation and verification by an expert dentist. The data collection process was carried out in the College of science, Gitam University. United Arab Emirates and a X-ray scanner was used for data collection.

Data Extraction and Interpretation:
In this stage, we systematically extracted information from each included study to address the initial research questions. Some attributes to be extracted vary depending on the specific research objective, emphasizing various computational methods utilized in the studies. In general, the following attributes were extracted: image dataset, including whether they were publicly available and their size; type of radiographic image being used; main project objectives, categorized into segmentation, classification, and detection; and computer techniques employed, categorized into deep learning, image processing, or classical machine learning.

Data preprocessing and annotation:

The annotation of dental caries requires pixel-level identification of the caries region and to accomplish this task we carefully designed a data annotation method that comprises three steps: (1)training of a data annotators team by a dental expert; (2) annotation of dental images by carefully following the guidelines provided by the expert; (3) validation and rectification of annotations by expert

The oral radiologist has more than 20 years of field experience and we considered only those annotations that were verified by him. We used a widely used tool named "Labelme" for annotating dental radiographs. Moreover, appropriate preprocessing was applied to all images to eliminate any privacy-related information. As it is very common in radiography to have patients' names on the X-ray image, such images were cropped to ensure the privacy of patients.

Performance analysis:

Performance metrics were used to compare the success of the developed deep learning models. In deep learning, the similarity between the values labeled on the test data (ground truth) and the predicted value of the model is measured by the IoU value. The object detection success of the model is evaluated by comparing the threshold and IoU values. In our study, the threshold value was set as 0.5.

The confusion matrix and the terminology used for the matrix in this study were as follows:

True Positive (TP): In the area where the object is labeled, the model indicates the object exists.

False Positive (FP): In the area where the object is not labeled, the model indicates the object exists.

False Negative (FN): In the area where the object is not labeled, the model indicates the object does not exist.

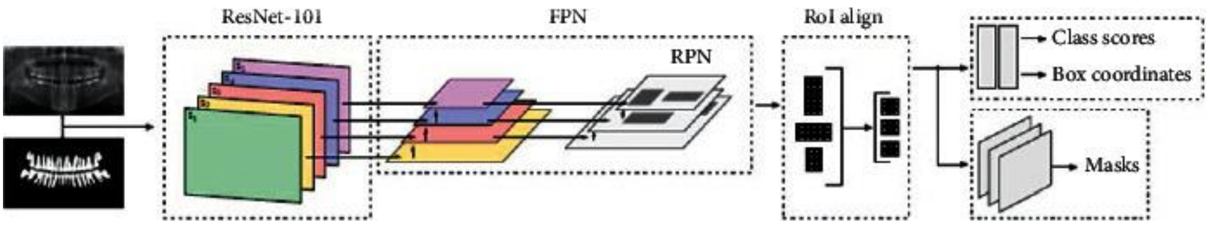
True Negative (TN): In the area where the object is labeled, the model indicates the object does not exist. TN value is generally not used in object detection.

After TP, FP, and FN values were obtained, model performance evaluation was made by calculating recall, precision, and F1 scores together with these values.

Precision (P) was the ratio showing how many of the positive predictions were correctly predicted. Recall (R) was the percentage of positive samples that are correctly predicted. The F1 score was the harmonic average of the P and R values reduced to a single number. It was used instead of accuracy. The mean average precision (mAP) is a metric used to evaluate the performance of a model for tasks such as information extraction and object detection.

Segmentation:

Segmentation is used to divide the image into distinct regions or segments based on the characteristics of the object of interest present in the image. Detection identifies and precisely locates objects within the image, generating an output in the form of bounding rectangles that surround the region of interest. Classification is a technique used to assign categories to an image, resulting in an output that indicates the association of the image with a specific category.



Splitting Data:

The data is split into training and testing data splits; for instance, Keras library for deep learning provides two ways of handling the splitting of data. It can split your data into a validation set and evaluate the performance of your model on that validation set. This is done by setting the validation split argument on the fit function to a certain percentage of your training dataset such as 30% for validation.

Training-Testing Split:

Data is split into two parts, training set and testing set. A model is then fitted to the training set, and then the fit model is used to make predictions on the testing set. This is further used to evaluate the skill of the predictions and thus referred to as the training-testing split. Training-testing split is used as an estimate of how well the model performs on a dataset, especially when presented with new data. This method is preferred, especially with very large data and slow model to train.

Deep Learning Methods and Algorithms

Neural Networks:

These are networks that contribute to deep learning systems. Neural networks consist of neurons with some activation *a* and parameters $\theta=\{W, \beta\}$, where W is weight and β is bias. Activation preselects the linear combination of input x to a neutron and its parameters, followed by element on element (.)

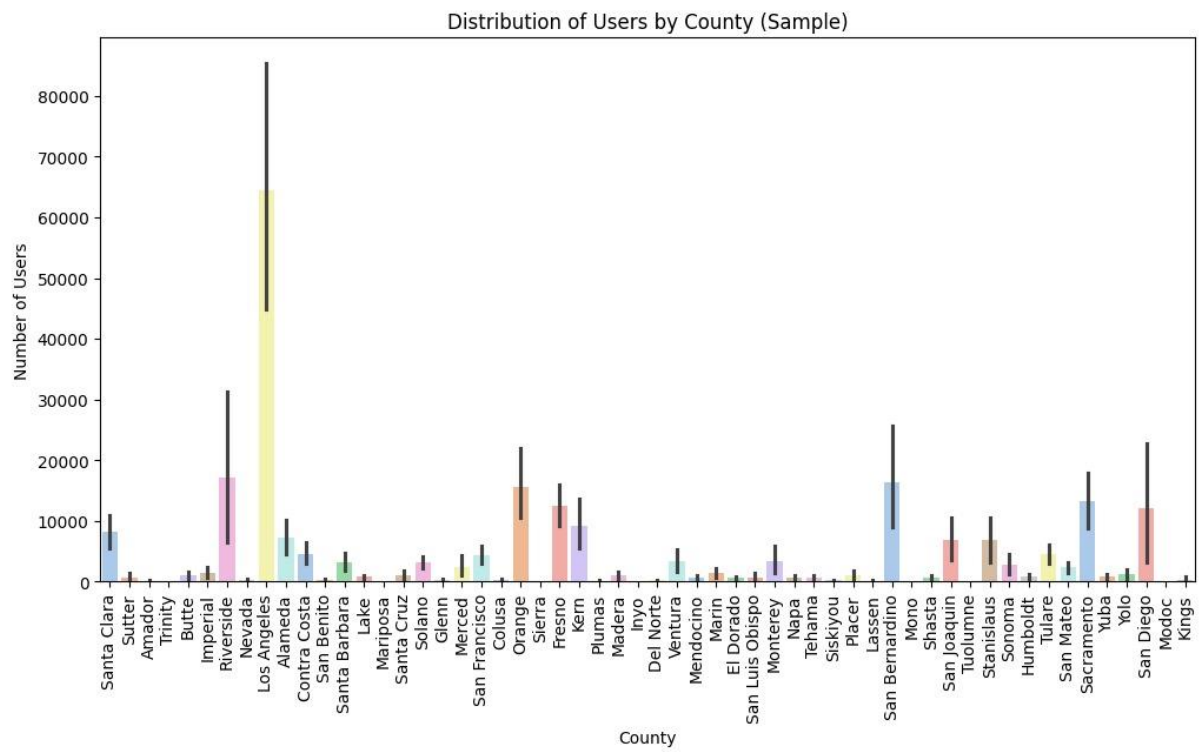
Convolution Neural Networks:

These networks have weights that are shared in a manner that the network performs convolutions on images. This means that there is no redundancy in the way the model learns separate detectors for the same object that occurs at different position on an image**.**

Recurrent Neural Networks:

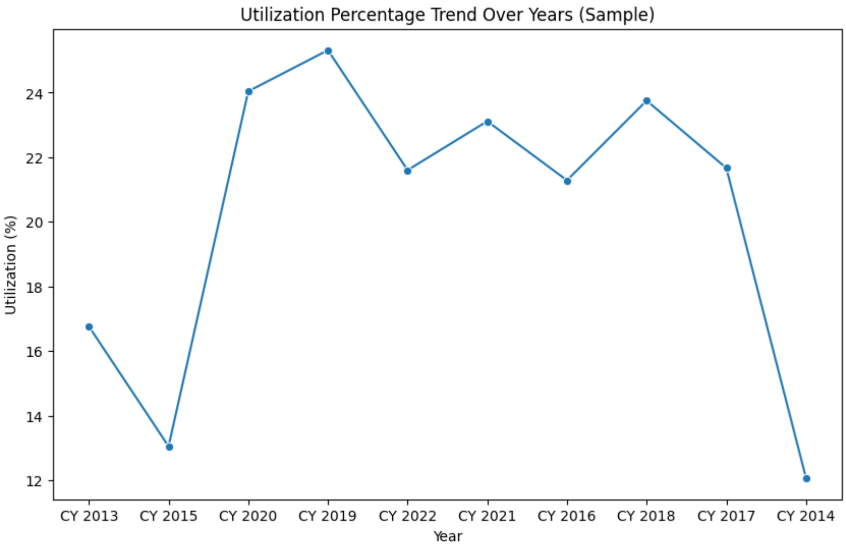
These networks were developed for discrete sequence analysis and have varied lengths for both inputs and outputs, thus making them suitable for tasks such as machine translation.

Graph representation:



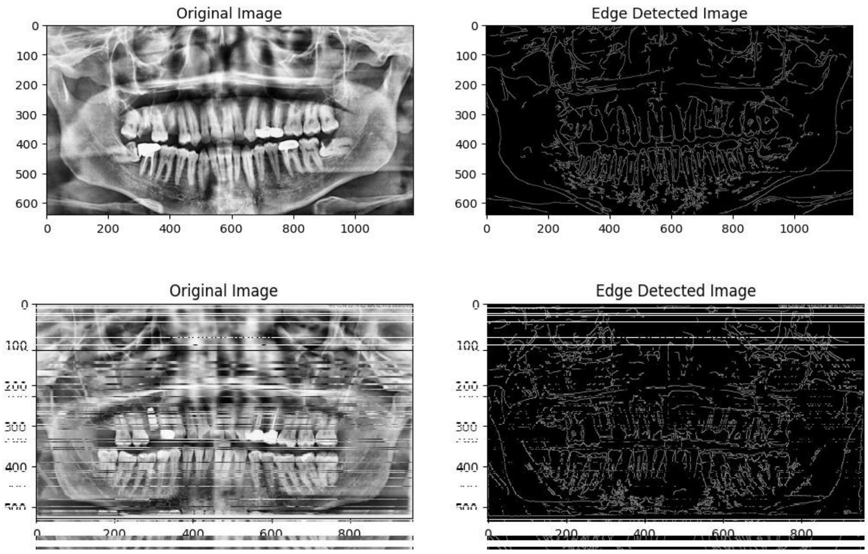
The above graph depicts the various countries and each country is labelled. The labels are represented vertically for good understanding. On y-axis number of users data is represented and on x-axis various countries is identified. The different colours of the graph represents represents various categories or datasets. Countries with lower population show lower count of information.

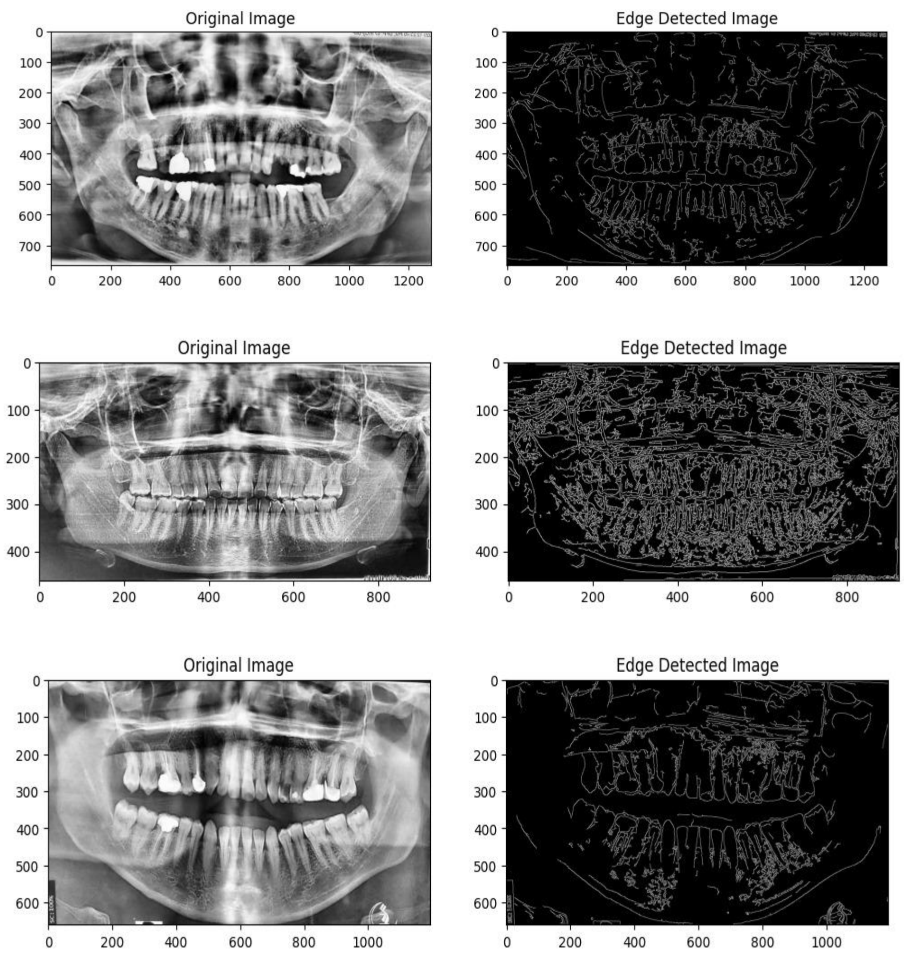
The datasets used in each study were classified as public or private. Datasets that offer open access were classified as public, while datasets without this access were categorized as private. Datasets in papers that intended to make data available, such as through contacting the author via mail but did not provide an external link for open access, were categorized as private.



The above graph shows the variations in utilization percentages across different years. On x-axis it represents years, and on y-axis represents utilization percentages ranging 12% to 25%. This shows the fluctuations of data of sharp drop between 2013 and 2015. Thrend shows the gradual decline when there is a lower utilization. The inconsistency indicates irregularities.

Related work:





The image contains a series of dental X-ray images (likely panoramic dental radiographs) paired with their corresponding edge-detected versions. Here's a detailed explanation:

Left Column: Displays the Original Image of dental X-rays. Each image shows a panoramic view of the upper and lower jaws, teeth, and surrounding structures.

Right Column: Displays the Edge Detected Image corresponding to each original image

Edge detection is a technique used in image processing to highlight the boundaries or edges of objects within the image

The edge detection method likely used here is Canny Edge Detection or a similar algorithm, which detects areas of rapid intensity change.

Key Observations:

Edge Detection Effect:

The edges of the teeth, jaw, and surrounding structures are highlighted in white on a black background. This helps in identifying the boundaries and shapes of objects in the X-ray more clearly.

Purpose: Edge detection is used in dental image analysis to Identify fractures, cavities, or abnormalities. Detect boundaries between teeth and gums. Enhance visualization of dental structures for better diagnosis.

Variations across Images: The images depict different dental X-rays, possibly of different patients or taken at different angles. Some edge-detected images show more noise or unwanted artifacts, likely due to variations in the original image quality.

Final remarks:

Computational methods: The SR identified studies that used several computational techniques to classify, detect, and segment dental caries, such as deep learning, machine learning, and image processing.
Datasets: The SR identified the datasets most commonly used in studies focusing on the diagnosis of dental caries.
Commonly used metrics: The SR metrics are frequently used to assess the effectiveness of methods in the diagnosis of dental caries, such as sensitivity, specificity, precision, AUC, ROC curve, Dice, and IoU.
Approximately 12% of the analyzed studies used public datasets while using deep learning accounted for 69% of the total works. The majority of these studies aimed to classify dental caries, either in binary or multiclass classification, comprising 76% of the total. Among the radiographic modalities, panoramic imaging was the most commonly used, representing 29% of cases, whereas CBCT had the lowest representation, with only 2%.

Future work:

Data availability and reliability: Deep learning networks require large amount of data to be able to achieve meaningful and effective performance results. Due to the nature of dental images, there is a need for hybrid datasets to aid good performance of the networks.

Data standardization: Many methods discussed here are handling the preprocessing step through manual methods, such as cropping the region of interest on an image. These methods contribute to the loss of some key details from the images.

Weight regularization methods: Deep learning networks can also be improved by introducing weight regularization to improve their performance. The regularization of weights involves optimization of model hyperparameters such as the learning rate and the dropout rate.

Hybrid approaches: Deep neural networks can also be achieved by combining several models or methods to form hybrid networks that will improve overall evaluation performance. The combination can be in any stage of the model, for instance, combining two preprocessing techniques to come with a single one to enhance image quality.

Conclusion:

From this survey, various techniques, methods, and approaches have been discussed concerning the segmentation and detection of dental images. Works that stem from the industry and academia have been mentioned and discussed, which include existing algorithms, segmentation and detection methods, databases, and various protocols for evaluating performance.

There is a huge potential for use of dental radiography and especially work focused on detection of dental images. Most of the existing systems dwell much on dental segmentation and not on feature extraction (detection). There is a need to improve existing dental detection systems, and one way to do so is by the introduction of automatic blob detection technique. Blob detection has been used in other fields of medical imaging but has not seen substantive use in the field of dental imaging. The use of such image analysis techniques to determine the presence of caries aims to create a system that takes a human diagnostic approach, whereby dental caries are diagnosed based on visual interpretation of teeth.

The main contribution of this work is the development of a complete case study for the dental caries detection in dental panoramic X-ray. Also, announced the availability of a new data set of panoramic dental X-ray images, which can constitute a tool for the research community in the development of stomatologic related applications. This data set has varying morphologic properties that make it valuable to the scientific community. These include the number of teeth perimage, the shape of the mouth and teeth as well as the levels of noise. Concerning the first two stages of the proposed method the results were considered satisfactory. These results regard each stage independently, which enabled us to perceive the actual merits of each module without corruption of the results due to errors in previous stages.

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