

A Three-Stage Caries Detection Approach From Radiographic Dental Images

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Abstract

Dental caries remains one of the most common and painful oral health issues globally. If not detected early, it can extend beyond the enamel, damaging the dental pulp and surrounding gum tissues, often requiring invasive and costly treatments. Traditional diagnostic techniques, such as Fiber-Optic Transillumination, visual inspection, and radiographic analysis, are heavily reliant on clinical expertise and are time-intensive. Therefore, an automated, efficient system to assist clinicians in accurately detecting caries boundaries from dental radiographs is both timely and necessary for improved treatment planning and monitoring.

In this context, we propose a novel three-stage method for caries lesion detection in dental radiographic images. The core principle is progressively reducing the computational area by removing irrelevant background regions at each stage, thereby lowering computational cost and energy consumption. In the first stage, a hybrid graph cut technique is used to remove non-essential regions and localize a rough area of interest. The second stage employs Grasshopper Optimization to refine the lesion boundary with greater precision. In the final stage, a modified level set method is applied to accurately delineate the caries-affected regions.

Experimental validation shows that the proposed method achieves an average accuracy of 90.62% across caries region detection. Although deep learning-based models may offer marginally better accuracy, they come with substantially higher energy and computational demands. The proposed method offers a balanced trade-off between accuracy and energy efficiency, making it well-suited for clinical environments where power consumption and processing resources are limited. These results affirm the potential of the proposed method as an effective, energy-efficient tool for early caries diagnosis.

Categories: Image Processing and Analysis, User-interface design for medical devices and healthcare software

Keywords: dental radiographic image, caries segmentation, adaptive histogram equalization, grasshopper optimization, level set, energy efficiency

Introduction

A significant proportion of both adults and children are affected by oral diseases, particularly dental caries. If left untreated, caries can progress into more complex and potentially life-threatening conditions. Therefore, early detection of caries lesions is essential [1]. However, detecting caries at an early stage poses several challenges:

a) Presence of different types of artifacts during taking oral imaging.

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- c) Tooth alignment is significantly different between individuals; hence, the segmentation process becomes quite complicated.
- d) Some patients have missing or impacted teeth.
- e) Teeth orientation differs from person to person.

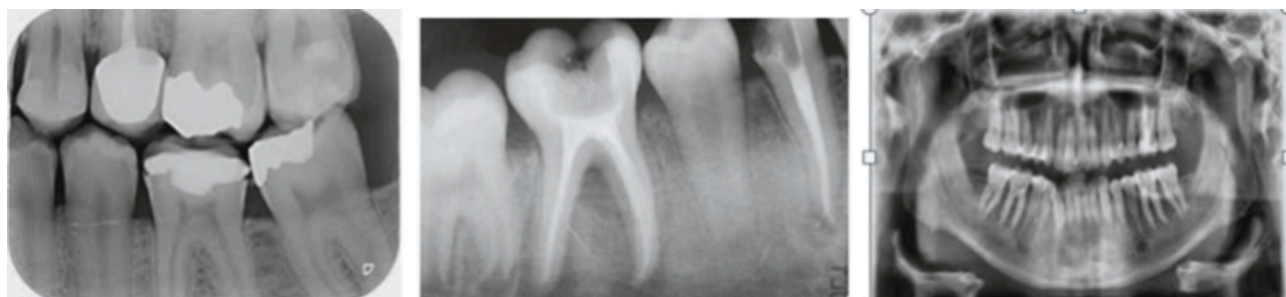


FIGURE 1: Dental X-ray images: types and variations

Existing caries detection techniques are not fully automated or patient-friendly and many suffer from high false-positive rates. For example, Electronic Caries Monitoring (ECM) often yields false positives due to tooth staining. Similarly, digital imaging fiber-optic transillumination (DIFOTI)-based imaging demands expert interpretation and expensive devices, while the quantitative light-induced fluorescence (QLF) system is complex and requires significant manual involvement. Although methods such as DIFOTI, QLF, and ECM are well-known [2,3], these still fail to detect hidden or inter-proximal caries - lesions those are not visible to the naked eye and may lead to severe complications if undiagnosed. In addition to these, DIFOTI, ECM, and QLF devices are heavy, expert-dependent, and prone to high false-positive rates. In such cases, dental practitioners typically rely on periapical and bitewing radiographs for evaluation. Dental X-ray imaging is extensively used to detect oral abnormalities. These images are obtained using relatively low radiation doses, which often result in poor-quality images that are susceptible to noise, increasing the likelihood of false negatives. Edge detection in such images is challenging, prompting the use of contrast enhancement, intensity correction, and noise-reduction algorithms to improve image clarity. Consequently, various computational and engineering tools have been employed to make dental X-ray image analysis more reliable. Dental X-rays are generally categorized into three types [4], briefly described below and illustrated in Figure 1:

- a) Bitewing X-rays: Bitewing X-rays focus on specific areas of the upper and lower jaws and are especially useful for detecting interproximal cavities and periodontal disease.
- b) Periapical X-rays: Provide a full view of each tooth from the enamel to the root, allowing detection of structural changes in the root and surrounding bone.
- c) Panoramic X-rays: Offer a comprehensive view of the entire mouth, including all teeth and supporting structures, and are commonly used in general diagnostics.

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FIGURE 2: Hidden dental caries in multiple teeth

Figure 2 illustrates the presence of hidden and inter-proximal caries in various tooth locations. Occasionally, dark areas observed in periapical or bitewing images are mistakenly identified as caries lesions. However, such dark regions can also appear in healthy teeth due to uneven X-ray exposure, sensor sensitivity variations, or differences in tooth thickness. Therefore, it is essential to segment these dark regions to improve diagnostic accuracy. Despite the availability of reliable diagnostic tools like dental probes, radiographic imaging remains the most widely used method for early screening and diagnosis. Dentists still rely on traditional approaches such as visual inspection, texture assessment, and discoloration detection. The proposed method is designed to be computationally lightweight. Its performance is evaluated using both accuracy-based metrics and efficiency-oriented considerations. For comparison, we used a VGG16 model pretrained on ImageNet as a deep learning baseline. This serves as an inference-only reference for resource-intensive convolutional neural network (CNN) approaches. Beyond segmentation accuracy, the pipeline demonstrates excellent computational efficiency with low energy consumption and reduced processing complexity. Occasionally, false positives arise in challenging cases, such as low-contrast regions or overlapping anatomical structures. Still, the results show a strong balance between accuracy and efficiency. Overall, this approach suits clinical environments with limited resources, while offering room for further improvements in robustness under tough imaging conditions. Within the existing literature, this work complements both classical image processing methods and recent deep learning approaches by addressing their respective limitations. While earlier handcrafted methods often lack robustness and full automation, and deep learning models require large datasets and high computational resources, the proposed approach offers a balanced alternative. By explicitly prioritizing computational and energy efficiency, the study contributes to sustainable medical image analysis and supports practical deployment in resource-constrained clinical environments. However, these methods are not foolproof, as their accuracy often depends on the practitioner's experience and subjective interpretation. The caries detection process generally follows two major steps. In the first step, the dental region is segmented from a non-uniform background consisting of gums and other soft tissues. Table 1 provides a comparative overview of existing methods and their limitations. In the second step, the actual caries lesion is identified within the previously segmented dental region. Table 2 offers a summary of widely used caries detection methods.

Related work

The analysis of dental radiography pictures has been the subject of numerous research projects. This section highlights a number of well-known current methods. By segmenting panoramic radiographs, Modi and Desai [5] presented a region-growing technique for dental segmentation that helps detect osteopenia and other dental problem. To improve clustering performance, Yin et al. proposed a semi-supervised entropy-regularized fuzzy clustering approach with additional parameter tuning ($u'k,j$), though its reliance on a predefined membership matrix restricts adaptability. Patanachai et al. [6] employed a wavelet-based segmentation framework for dental X-ray images, enabling effective pixel-wise feature marking and edge detection, and validated their model using data from the Faculty of Dentistry, Chulalongkorn University. In a related effort, a texture-based fuzzy inference system achieved 82% segmentation accuracy on dental radiographs [7]. More recently, Arora et al. [8] developed a fully convolutional neural network for bitewing image segmentation, reporting 95% accuracy on a dataset of 3,000 images. Despite these advances, existing methods often suffer from high false-positive rates, dependence on large annotated datasets, increased computational

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and energy costs, and limited end-to-end automation-gaps that the proposed method aims to address. Choi et al. [9] proposed a four-stage automatic caries detection framework that includes crown extraction, probability map generation, fine-tuning, and horizontal alignment of dental X-ray images. The approach combines a fully convolutional network with an edge-wise level set technique and is further refined using non-maximum suppression. Despite their effectiveness, such multi-stage methods often suffer from high false-positive rates, dependence on large annotated datasets, increased energy consumption, and limited end-to-end automation-gaps that the proposed method aims to address. Li et al. [10] developed an automated lesion detection framework using two coupled level set functions, where an SVM-based initial contour generation was employed to segment caries lesions. Jain and Chen [11] proposed a semi-automatic contour extraction approach consisting of contour matching, pixel classification, and radiograph segmentation. Their method was tested on only 38 images and showed limitations in handling blurry, rotated, or partially visible teeth. Nomir and Abdel-Mottaleb [12] proposed a segmentation method combining iterative and adaptive thresholding for bitewing images, followed by vertical and horizontal integral projections to isolate individual teeth. They validated the approach on 162 dental bitewing radiographs, though its time complexity ($O(n^2)$) presents a performance concern. Naebi et al. [13] introduced a fully automated technique for caries detection using mathematical formulations and particle swarm optimization. While the method effectively segments lesions and offers reconstruction, it is limited to 2D images and fails to perform on noisy 3D data [13]. Lee et al. [14] presented a transfer learning-based caries detection method using a pre-trained GoogLeNet Inception V3 CNN. The model, which includes 22 layers and nine inception modules, was trained over 1000 iterations using 3000 periapical images, with 2400 used for training and 600 for validation. The images were resized to 299×299 pixels to reduce computational demands, though this could potentially result in loss of critical image details [14]. Singh and Sehgal [15] proposed a hybrid CNN-LSTM approach for detecting six types of caries lesions from periapical images, based on the G.V. Black classification system. Siva Kumar [16] employed power spectrum and histogram analysis to identify early-stage caries lesions. Their findings suggested that the histogram and frequency components differ significantly between healthy and affected teeth. The segmentation was performed solely using histogram-based techniques, which limits reliability in cases involving filled or crowned teeth [16]. Tables 1 and 2 provide comparative summaries of the dental image segmentation and caries lesion detection methods, respectively. These highlight the strengths and limitations of existing approaches in terms of datasets, functionality, image types, and performance.

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Reference	Used Segmentation Technique	Dataset	Functionality	Type of Dental X-ray Images	Accuracy	Challenges
[6]	Wavelet transformation	Collected from Dentistry Hospital, Chulalongkon University	Individual tooth extraction from selected teeth region	Panoramic dental X-ray	82%	Bit slow as it uses wavelet transformation
[10]	Convolution neural network (CNN)	3,000 benchmarked database	Individual tooth segmentation	Bitewing	95%	Works well but needs a large amount of data to pre-train the model
[12]	Iterative thresholding followed by adaptive thresholding	Standard AM, PM dataset	Individual tooth segmentation	Bitewing	Accuracy not reported in original study	It is not automatic. There must be manual involvement
[17]	Semi-supervised fuzzy clustering	Real dataset collected from Hanoi Medial University, Vietnam	Interactive fuzzy satisficing-based semi-supervised fuzzy clustering technique	Bitewing	Accuracy not reported in original study	The teeth region is correctly extracted using this procedure. It occasionally overlooks the pulp area and caries lesion. As a result, this approach cannot be used to identify some diseases, such as dental cavities
[18]	Region growing	CJIS	Entire teeth segmentation	Periapical	83%	When there are several variations in the illumination and contrast of the input image, the findings are incorrect
[19]	CNN	Cityscapes database	Entire teeth segmentation	All types of images	88%	Works well but needs a large amount of data to pre-train the model

TABLE 1: Summary of different caries lesion segmentation techniques

Reference	Used Segmentation Technique	Dataset	Functionality	Type of Dental X-ray Images	Accuracy	Challenges
[16]	Power spectrum and histogram analysis	Data are collected from internet	Caries detection	Bitewing	83%	It is not transparent and does not provide accurate result
[13]	Particle swarm optimization and mathematical formulation	2D X-ray images are collected from internet	Caries lesion detection	Periapical X-ray images	92%	Requires huge computations
[20]	Isophote and Geodasic active contour	Digital dental periapical X-ray database for caries screening, digital dental X-ray image dataset along ground truth	Caries lesion detection along with individual tooth segmentation	Bitewing X-ray images	90%	Does not work when missing teeth or other abnormalities are present
[10]	Two coupled level set functions		Caries lesion detection	Bitewing, periapical	85%	Datasets are insignificant
[14]	Pretrained GoogLeNet Inception V3 CNN and transfer learning	3,000 periapical standard data	Caries lesion detection	Periapical X-ray images	89%	It is not flexible, and output images are prone to noises

TABLE 2: Summary of different caries lesion segmentation techniques

CNN, Convolutional Neural Network

Despite their contributions, many of the above-mentioned techniques suffer from high false-positive rates and segmentation errors. Most are not well-suited for fully automated caries detection. The proposed method aims to overcome these issues. Initially, adaptive histogram equalization is applied to enhance X-ray image quality and suppress noise. The segmentation process is then executed in two levels: the first level applies a hybrid graph cut method, while the second level uses grasshopper optimization for refined tooth segmentation. Finally, the level set method is employed to delineate the boundary of caries lesions.

The main contributions of this research are summarized as follows:

1. A two-phase segmentation approach is proposed, combining grasshopper optimization and hybrid graph cut, followed by level set-based boundary extraction. This method is capable of segmenting proximal and inter-proximal caries lesions in both molar and premolar teeth.
2. Experimental validation on a benchmark dataset demonstrated over 91% accuracy, satisfying clinical requirements for dental caries detection.
3. The proposed technique is fully automated and requires no manual initialization. It effectively handles a wide range of lesion sizes and complex conditions.

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Materials And Methods

The block diagram shown in Figure 3 represents the architecture of the proposed three-stage dental caries detection system using radiographic images. It begins with the input of grayscale or RGB-format dental X-ray images, along with ground truth information for evaluation purposes. RGB images are first converted to a standardized two-dimensional grayscale format. In the preprocessing stage, adaptive histogram equalization (AHE) is applied to enhance image contrast and eliminate irrelevant details, thereby reducing the computational burden. A hybrid graph cut method is then used to perform rough segmentation of the region of interest (ROI), narrowing down the area requiring further analysis. This is followed by a refined segmentation phase, where grasshopper optimization is employed to accurately delineate the teeth structure. Subsequently, the caries lesion boundaries are precisely identified using a level set method. The final segmented output image is then generated. To assess performance, the segmented results are compared against the ground truth and alternative techniques [10-12] using well-established evaluation metrics. The system concludes by generating a comprehensive comparison report to validate the efficiency and accuracy of the proposed method. The input images may contain various types of noise, requiring a preprocessing step before segmentation. Each step is described below in detail.

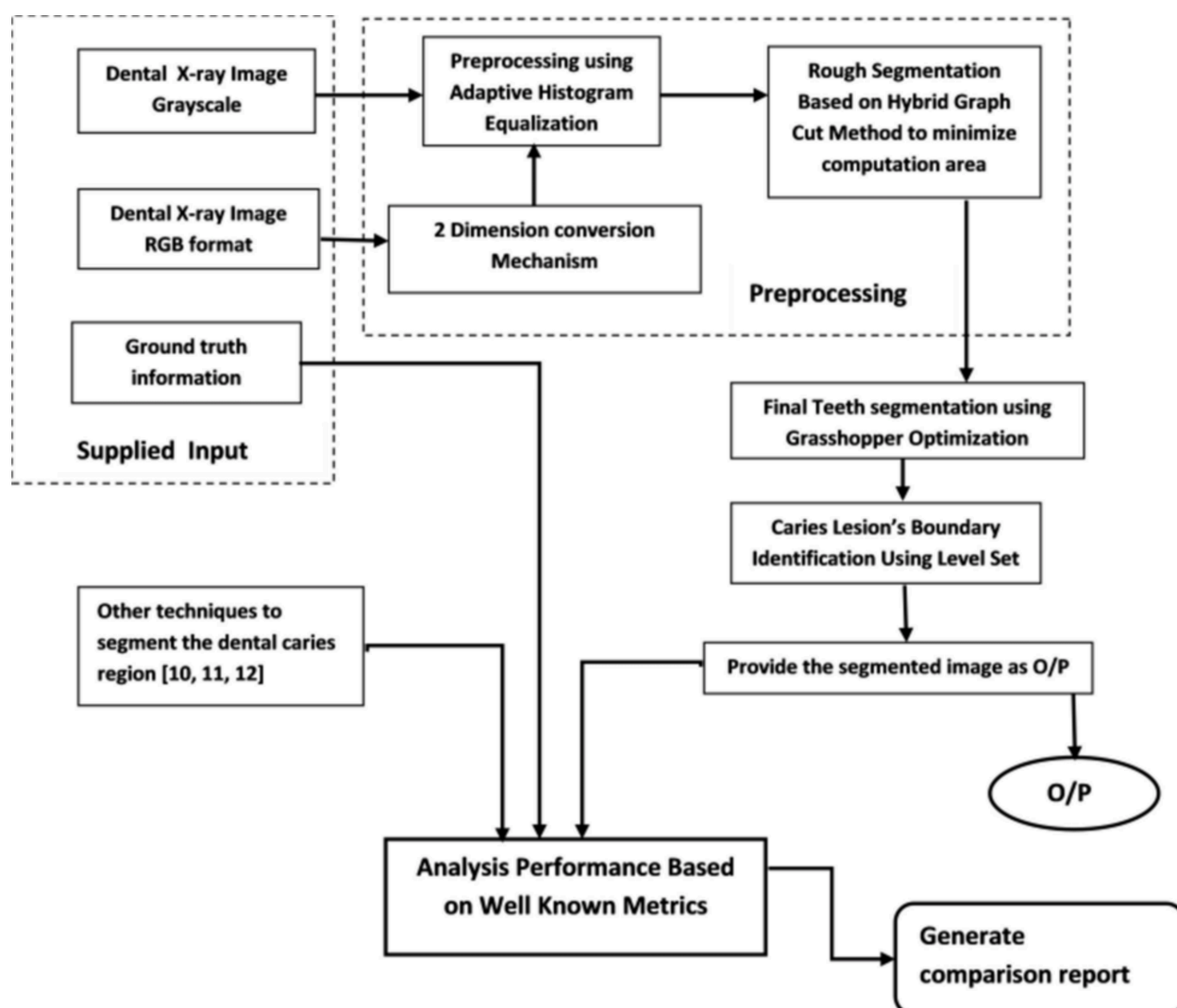


FIGURE 3: Block diagram of the proposed method

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Preprocessing

The block diagram contains main three phases like (1) AHE + hybrid graph cut ROI, (2) grasshopper optimization for tooth structure, and (3) level set for caries boundary. This AHE technique is step-wise described in Procedure 1. The histogram of the input dental X-ray image is computed, and pixel intensities are adjusted relative to their neighborhood to improve local contrast. This technique helps isolate critical features while reducing the computational overhead in subsequent stages.

Procedure 1: Adaptive histogram equalization algorithm

Purpose: To enhance the contrast of local regions in a grayscale image by computing a histogram-based intensity transformation for each pixel's neighborhood. This technique improves visibility of structures in low-contrast regions, making it particularly suitable for medical imaging like dental X-rays.

Input: Grayscale image with pixel intensities $g(j)$, neighborhood window size $w \times w$

Output: Preprocessed image with enhanced local contrast

Step 1: For each pixel i in the image (with gray level l) repeat steps 2 to 5: Initialize histogram array:

$$Hist[k] \leftarrow 0 \quad \text{for all } k \in [0, L - 1] \quad (1)$$

Step 2: For each contextual pixel j in the local neighborhood of i repeat step 3 to 4: Increment histogram count for its intensity value:

$$Hist[g(j)] \leftarrow Hist[g(j)] + 1 \quad (2)$$

Step 3: Compute the cumulative histogram for gray level l :

$$CHist_l = \sum_{k=0}^l Hist(k) \quad (3)$$

Step 4: Calculate the new gray level l' for pixel i :

$$l' = CHist_l \times \frac{L}{w^2} \quad (4)$$

Here, L is the Maximum Intensity Level (0-255).

Step 5: Replace the original intensity l of pixel i with new gray level l'

Step 6: Stop

In the preprocessing phase, AHE [21,22] is applied to enhance image contrast and suppress noise. AHE is a local contrast enhancement technique used in medical image pre-processing. In this method, the intensity of each pixel is adjusted based on the statistical distribution of intensities within its local neighborhood. For a pixel i , the algorithm constructs a histogram of the surrounding window (contextual pixels), denoted by $g(j)$, where j indexes neighboring pixels. The cumulative histogram value $CHist_i$ is then calculated up to the gray level l of the center pixel. This cumulative count is scaled by the number of gray levels L and normalized by the window size w^2 to produce the new intensity l' . This localized adjustment enhances fine details and improves visibility in low-contrast dental X-ray images, making it easier to distinguish tooth structures and lesions. As shown in Figure 4, the pre-processing step results in improved contrast (4b) and a more uniformly distributed histogram (4c), when compared to the original image (4a).

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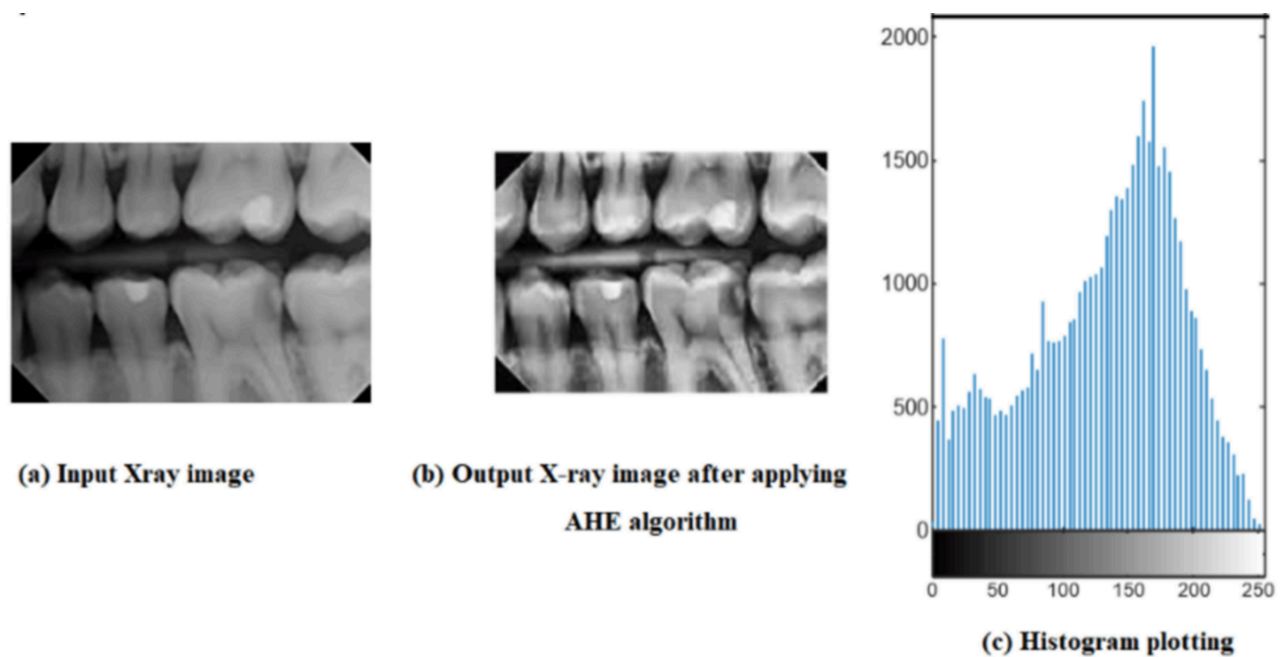


FIGURE 4: (a) Input bitewing dental X-ray image. (b) Preprocessed image after AHE. (c) Histogram representation of the preprocessed image

AHE, Adaptive Histogram Equalization

The AHE algorithm works as, for each pixel i with gray level I , a local histogram is initialized and updated by counting the intensity values of all contextual pixels j within its neighborhood. Using this histogram, the cumulative distribution up to gray level I is computed, and a new gray level I' is obtained based on the cumulative histogram and the maximum intensity level $L(0-255)$. Finally, the original intensity I of pixel i is replaced with the new value I' and the process is repeated for all pixels until completion.

Segmentation based on hybrid graph cut

In the first stage of segmentation, the hybrid graph cut algorithm is employed to identify a rough ROI. Graph cut techniques have proven effective in segmenting medical and natural images [23,24]. Using this method, an image can be expressed as an undirected graph $G = \{V, E\}$, where V stands for the set of pixels (nodes) and E for the edges that connect adjacent pixels. The foreground and background are represented by two unique terminal nodes, source (s) and sink (t), respectively. Edges are classified as either t-links (between pixels and terminals) or n-links (between adjacent pixels). The algorithm utilizes the max-flow/min-cut theorem to minimize the sum of weights (cost) on the cut edges after computing a "cut" that divides the graph into two disjoint sets S and T ($s \in S, t \in T$).

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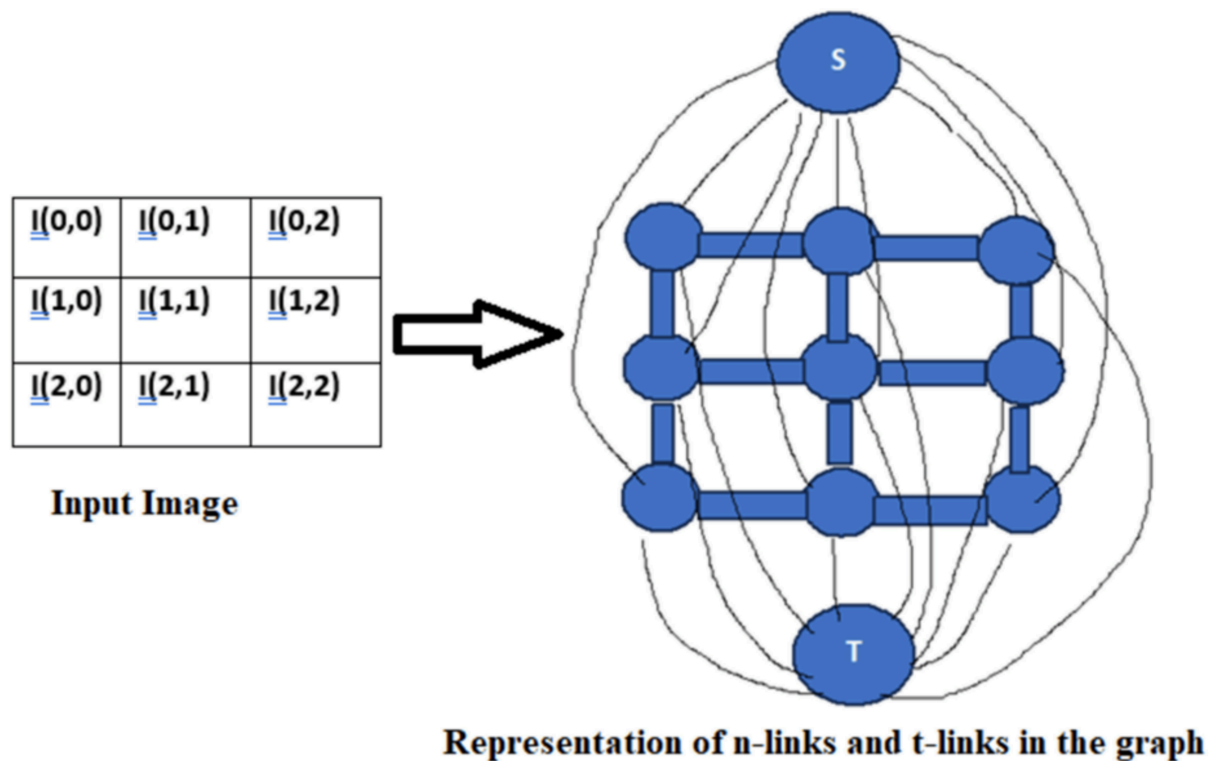


FIGURE 5: Representation of s-t graph. Thick blue lines indicate n-links, and thin black lines indicate t-links

It has been observed that the graph cut technique yields effective segmentation results, particularly for images containing multiple distinct objects [23,24]. This method is widely used for extracting ROI in both medical and natural images. Let G be an undirected graph represented as $G = \{V, E\}$, where V denotes the set of vertices (corresponding to image pixels), and E represents the set of edges connecting neighboring vertices. The graph includes two special types of nodes: the source (s) and the sink or terminal (t), forming what is commonly referred to as an s-t graph. When modeling an image as an s-t graph, the source s corresponds to the foreground region, and the sink t corresponds to the background. Edges in this graph are categorized as n-links (connecting neighboring pixels) or t-links (connecting pixels to source or sink terminals). In the graph-cut framework, pixels are connected to either source or sink terminals. A cut is defined as a subset of edges $c \subseteq E$ whose removal partitions the graph into two disjoint subsets. The cost of a cut is computed as the sum of the weights of all edges belonging to the cut set and is formally given in Equation (5). In this equation, E denotes the set of all edges in the graph, c represents the selected cut, and w_e is the weight associated with edge e .

$$|c| = \sum_{e \in c}^n w_e \quad (5)$$

Most of the time, our target will be to minimize this cost function. It could be achieved by maximizing the flow. Standard max flow/min cut algorithm is used to generate the cut for source-link graph. At first, this cut c separates the graph into two disjoint halves S and T and maintains the relations $s \in S, t \in T$, and $S \cup T = V$. These two halves represent the background region and the segmented foreground region. The pictorial representation is shown in Figure 5.

Final teeth segmentation using grasshopper optimization

In the second stage, we apply the modified grasshopper optimization algorithm (GOA) [25-27] to refine the segmentation of teeth structures. Inspired by the natural swarming behavior of grasshoppers, this metaheuristic technique models social interaction, gravitational force, and wind advection to explore and exploit optimal solutions in the search space.

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The algorithm evaluates candidate solutions based on a fitness function and iteratively adjusts positions to converge on the optimal solution. The swarming behavior of grasshoppers in the wild served as the model for the GOA. This method was put forth by Mirjalili et al. [28] to determine the ideal form for architectural constructions. The three primary determinants of improved grasshopper locomotion are gravitational force GF_i , wind advection WA_i , and social interaction SI_i . The representation for the i th grasshopper X_i is depicted as follows:

$$X_i = GF_i + WA_i + SI_i \quad (6)$$

$$SI_i = \sum_{j=1, j \neq i}^N S(|X_j - X_i|) \frac{x_j - x_i}{a_{ij}} \quad (7)$$

Here, S is a function.

$$S(t) = k \cdot e^{\frac{1}{n}} - e^t \quad (8)$$

Here, n and l are constant, a_{ij} is a normalization factor, and $x_j - x_i$ is the vector difference in position from agent i to agent j .

$$d_{ij} = X_j - X_i \quad (9)$$

Here, $X_j - X_i$ is an influence function that depends on distance d_{ij} .

N is the quantity of grasshopper in the swarm. Gradient force GF_i is defined as per Equation (9).

$$GF_i = -gr * e \hat{g} r \quad (10)$$

Here, gr is the constant and $e * \hat{g} * r$ is the unity vector.

According to equation [28], Equation (7) would be updated to fit the exact condition of grasshopper's movement, and it is presented as

$$X_i^k = K \left(\sum_{j=1, j \neq i}^N K \frac{ub_k - lb_k}{2} S \left(|X_i^k - X_j^k| \frac{X_j - X_i}{d_{ij}} \right) \right) + T_k \quad (11)$$

Here, lb_k and ub_k are the lower bound and upper bound in the k th dimension. X_i^k represents the position of the i th agent in the k th dimension. K is the scaling constant. T_k is the value of k th dimension in the target. The coefficient k is presented as follows:

$$K = K_{\max} - i \times \frac{K_{\max} - K_{\min}}{l_m} \quad (12)$$

Here, i is the loop at the current scenario. l_m is the upper limit of the loop. $K_{\max} = 1$ and $K_{\min} = 0.0001$

Procedure 2: Modified grasshopper optimization technique

Purpose: To enhance the contrast of local regions in a grayscale image by computing a histogram-based intensity transformation for each pixel's neighborhood. This technique improves visibility of structures in low-contrast regions, making it particularly suitable for medical imaging like dental X-rays.

Input: N - Population size (number of grasshoppers), $K_{\max}$, $K_{\min}$ - Maximum and minimum values for control parameter K , l_m - Maximum number of iterations.

Output: A: The best solution found, i.e., the best search agent.

Step 1: Initialize a swarm of N grasshoppers with random positions representing candidate segmentation parameters.

Step 2: Set the algorithm parameters $K_{\max}$, $K_{\min}$, and the maximum number of iterations l_m .

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Step 3: Evaluate the fitness of each grasshopper using the segmentation objective function, defined to minimize boundary energy and maximize overlap with the initial contour obtained from the level set method, and assign the best solution as A .

Step 4: Repeat Steps 5-8 until the iteration counter i reaches Im .

Step 5: Update the control parameter K using Equation (12).

Step 6: For each grasshopper, normalize the distance with respect to other grasshoppers and update its position using Equation (11); if the updated position exceeds the search bounds, project it back into the valid segmentation parameter space.

Step 7: Re-evaluate the fitness of all grasshoppers based on the segmentation objective; if a solution with lower boundary energy or higher region consistency is found, update A .

Step 8: Increment the iteration counter $i = i + 1$.

Step 9: Stop when the optimal segmentation parameters are obtained.

Procedure 2 explains all the steps of modified GOA. Inspired by the swarming behavior of grasshoppers in nature, the modified GOA [29] is described in Procedure 2. The algorithm begins by initializing a swarm of candidate solutions (grasshoppers) and iteratively adjusts their positions based on social interaction, gravitational forces, and wind advection to converge toward the optimal solution. At each iteration, the control parameter K is dynamically updated, and the positions of the grasshoppers are refined using Equations (11) and (12). The best-performing solution, based on fitness evaluation, is continuously updated, making GOA a powerful and adaptive method for fine-grained image segmentation tasks.

Boundary detection of caries lesion using level set technique

The level set segmentation technique, originally proposed by Vese and Chan [30,31], is extensively used for segmenting a wide range of images, especially in medical imaging. This method allows dynamic contour evolution with robust tracking capability and effectively handles topological changes such as merging or splitting of regions. Figure 6 illustrates the evolution of a contour in three-dimensional space, where the z -axis represents the level set function $\phi(x, y, z)$, which captures the interface movement during the segmentation process.

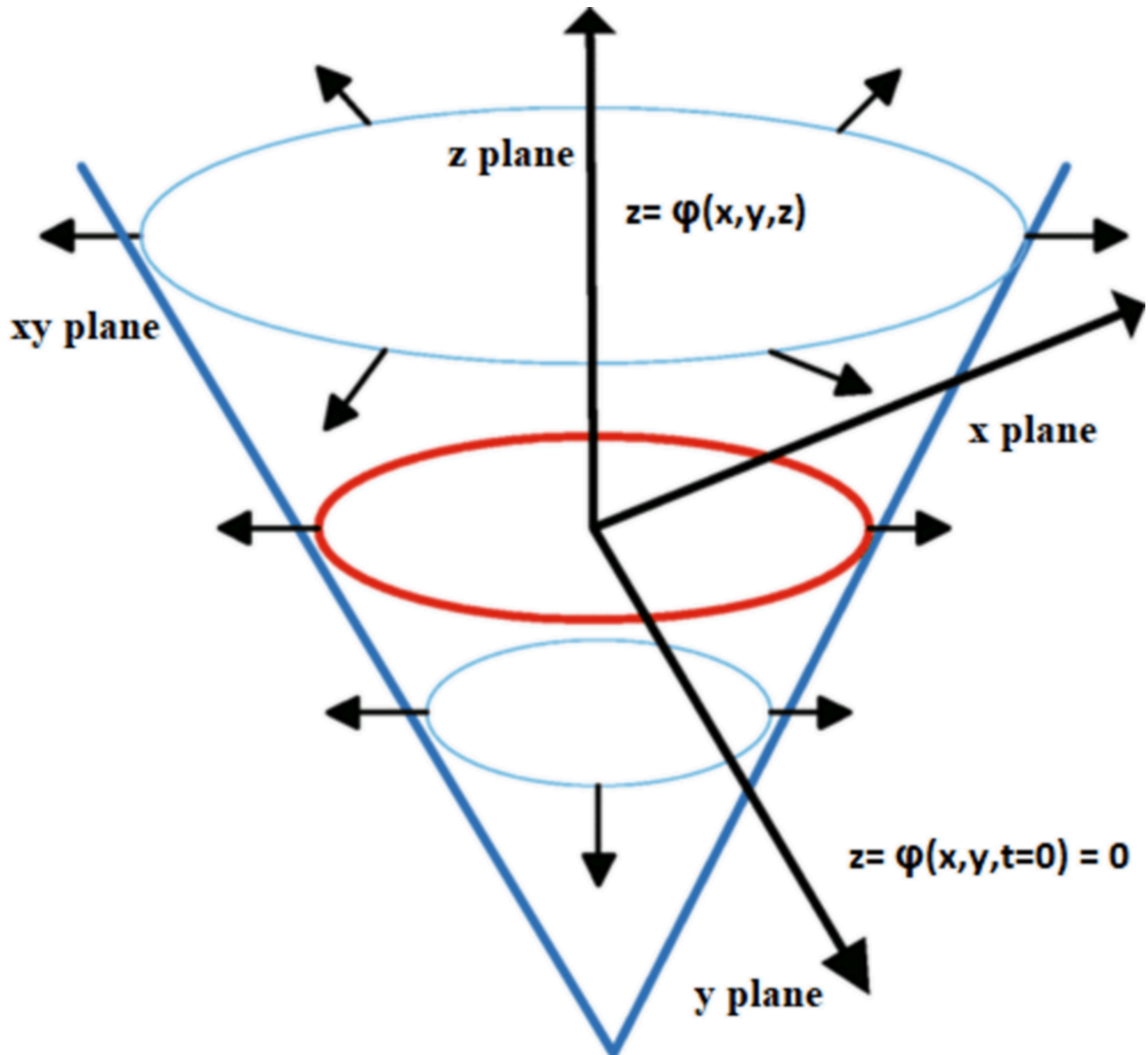


FIGURE 6: Curve is growing in 3D space where z-axis presents the function $\phi(x, y, z)$

The level set function is defined at each spatial coordinate (x, y) and corresponds to the height of the z-function. It represents a dynamic contour that expands or contracts based on a curvature-dependent speed function, allowing the contour to propagate over time. In certain cases, the method incorporates the Hamilton-Jacobi equation to model and evolve more complex and irregular shapes effectively.

$$z = \phi(x, y, z) \quad (13)$$

Let we assume that a domain D is divided using a contour $C = \{ \phi(x) = 0 \}$ into two possible non-connected small regions $D_{in} = \{ \phi(x) > 0 \}$ and $D_{out} = \{ \phi(x) < 0 \}$. The function ϕ is defined as level set function of segmenting different contours [32]. Let $Img(x)$ be an image defined over the domain D . This method relies on minimizing an intensity-based energy function, as given in the following Equation (14).

$$Energy(\emptyset, C_1, C_2) = |C| + \int_{D_{in}} |img(x) - C_1|^2 dx + \int_{D_{out}} |img(x) - C_2|^2 dx \quad (14)$$

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Here, $|C|$ represents the length of the segmented contour, while C_1 and C_2 denote the average intensities inside and outside the contour C , respectively, as defined by the following Equations (15) and (16), respectively. D_{in} and D_{out} represent the region inside contour and outside contour, respectively.

$$C_1 = \frac{1}{|D_{in}|} \int_{D_{in}} Img(x) dx \quad (15)$$

$$C_2 = \frac{1}{|D_{out}|} \int_{D_{out}} Img(x) dx \quad (16)$$

In the previous Equations (15) and (16), the energy function penalizes local deviations from the average intensity within the segmented regions. The level set segmentation technique is preferred because it is fully automated, less sensitive to noise, and easily extendable to higher dimensions.

Results

The proposed method consists of two primary phases. The first phase focuses on segmenting the teeth region from a non-uniform background, while the second phase is dedicated to identifying the precise caries-affected lesions. Accordingly, this section is divided into two subsections to separately evaluate and present the performance of each phase.

Database description

The proposed method was validated using two publicly available datasets: the Database for Caries Screening [33] and Panoramic Dental X-rays With Segmented Mandibles [34]. The limited availability of large and diverse dental radiography datasets remains a major challenge for comprehensive validation in this domain [32,35]. The Database for Caries Screening comprises 120 periapical radiographs collected from different sources, including 72 normal or post-treatment images, 37 images exhibiting anomalies such as untreated acute caries lesions or cysts, and 11 images with missing teeth. All images have a resolution of 748×512 pixels and are stored in JPEG format. The Panoramic Dental X-rays With Segmented Mandibles dataset contains 116 panoramic radiographs acquired from 116 participants at the Noor Medical Imaging Center, Qom, Iran, of which 45 images show minor abnormalities and 12 exhibit missing teeth. These images have a resolution of $3,150 \times 1,250$ pixels and are provided in PNG format. Both datasets include expert-annotated ground truth images corresponding to caries lesions and segmented mandibles. The Database for Caries Screening was used exclusively for caries detection experiments, while the Panoramic Dental X-rays With Segmented Mandibles dataset was used for tooth/mandible segmentation. No cross-dataset evaluation was performed; each dataset was evaluated independently for its intended task. Since the proposed approach is a handcrafted segmentation method and does not involve a learning phase, all available images from both datasets were used exclusively for testing to ensure a fair comparison with learning-based methods reported in the literature. The segmentation performance for isolating the teeth region was evaluated using the Dice Similarity Coefficient (DSC) and the Jaccard Index (JI) [36,37]. The DSC measures the degree of overlap between the segmented output and the ground truth, while the JI quantifies the ratio of their intersection to their union. In Equations (17) and (18), the area denotes the number of common pixels shared between the segmented and ground truth regions.

Teeth region segmentation from non-uniform background

The effectiveness of the proposed image segmentation model for isolating the teeth region was evaluated using the DSC and JI [36,37]. The DSC quantifies the similarity between the segmented output and the ground truth by considering the overlap between them. The JI measures the proportion of the intersection to the union of the predicted and reference segmentations.

$$DSC = \frac{2 * area}{Total_number_of_pixel_in_both_images} \quad (17)$$

In Equation (18), area represents the number of common pixels between the segmented and ground truth regions.

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$$JI = \frac{Area_of_Overlap}{Area_of_Union} \quad (18)$$

In addition to these, the model's performance was further assessed using sensitivity and specificity [32], which provide insight into the model's ability to correctly identify true positives and true negatives, respectively. These are defined as follows:

$$Sensitivity = \frac{Number_of_True_Positive}{Number_of_True_Positive + Number_of_False_Positive} \quad (19)$$

$$Specificity = \frac{Number_of_True_Negative}{Number_of_True_Negative + Number_of_False_Positive} \quad (20)$$

In both Equations (19) and (20), True Positive determines the number of correctly predicted affected lesions. False Negative represents the number of actual affected lesions that are not detected. False Positive represents incorrectly predicted affected lesions. True Negative calculated correctly identified unaffected lesions. The JI was also used to compare the predicted bounding box with the gold standard bounding box. A predicted bounding box was considered a successful match if the JI score exceeded 0.7. Finally, these metrics were employed to comprehensively evaluate the effectiveness of the proposed tooth segmentation and numbering approach.

$$Detection_Precision = \frac{N_{successful(match)}}{N_{detected(bounding_box)}} \quad (21)$$

$$Detection_Recall = \frac{N_{successful(match)}}{N_{gold(standard_bounding_box)}} \quad (22)$$

Image Type	Number of Cases	Images Volumes	Segmented Region	Dice Similar Coefficient (mean+SD/mean-SD)	Jaccard Index (mean+SD/mean-SD)
Periapical	50	550	Bone Area	0.95 ± 0.0027	0.89 ± 0.0125
	50	550	Tooth Area	0.94 ± 0.015	0.84 ± 0.0012
	50	550	CEJ Line	0.92 ± 0.0459	0.89 ± 0.0425
Panoramic	60	60	Tooth Area	0.93 ± 0.0995	0.89 ± 0.0059

TABLE 3: Dice Similarity Coefficient and Jaccard Index for segmentation models

SD, Standard Deviation

The DSC and JI metrics were used to evaluate the performance of the segmentation models. As shown in Table 3, the segmentation models were repeatedly run with different random seeds to compute the mean and standard deviation of the DSC and JI on the test data. The average DSC score of the segmentation models for both panoramic and periapical radiographs exceeds 0.93. The proposed method achieved an average DSC greater than 0.93 across the evaluated datasets, with a low standard deviation (±0.01-0.02), indicating consistent segmentation performance across different images. This low variance demonstrates the robustness and stability of the proposed approach under varying image conditions.

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Table 4 presents a comparative analysis based on mean squared error (MSE), DSC, specificity, sensitivity, and accuracy [38-41]. Although the average accuracy of the proposed technique (90.63%) is slightly lower than that of the ImageNet-16 method (91.20%), training and testing the ImageNet-based approach is computationally intensive, making the proposed method more efficient in practice.

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Name of the Method	Dataset	Specificity	Sensitivity	Accuracy	Dice Similarity Coefficient	MSE
Geodesic active contour technique	Sample_1	79.76	76.56	82.67	0.23	71.79
	Sample_2	80.12	77.89	80.67	0.21	73.25
	Sample_3	82.35	77.9	81.9	0.24	72.67
	Sample_4	81.9	78.88	83.87	0.25	76.78
	Average_value	81.0325	77.8075	82.2775	0.2325	73.6225
FAFCM	Sample_1	85.78	80.87	81.27	0.24	78.9
	Sample_2	89.67	82.78	80.78	0.19	77.78
	Sample_3	90.56	79.89	80.19	0.31	80.71
	Sample_4	87.67	81.56	82.9	0.28	81.79
	Average_value	88.42	81.275	81.285	0.255	79.795
Watershed technique	Sample_1	69.53	70.79	72.56	0.35	67.8
	Sample_2	70.78	72.34	71.45	0.32	69.71
	Sample_3	71.9	71.78	75.67	0.25	70.72
	Sample_4	70.87	72.65	73.79	0.31	71.23
	Average_value	70.77	71.89	73.3675	0.3075	69.865
ImageNet with 16 layers	Sample_1	91.32	91.86	90.78	0.24	81.67
	Sample_2	89.9	89.79	91.88	0.3	81.89
	Sample_3	90.54	90.27	89.45	0.22	83.67
	Sample_4	93.21	93.56	92.67	0.25	81.67
	Average_value	91.2425	91.37	91.195	0.2525	82.225
Proposed technique	Sample_1	89.78	90.9	90.71	0.21	73.54
	Sample_2	90.87	90.79	91.92	0.23	79.55
	Sample_3	90.34	89.67	90	0.28	80.61
	Sample_4	93.45	91.34	89.88	0.26	82.46

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	Average_value	91.11	90.675	90.6275	0.245	79.04
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TABLE 4: Comparative study between the proposed method and existing methods

MSE, Mean Squared Error

Figure 7 shows the segmented teeth from periapical dental X-ray images. Figure 8 presents a comparative study between the proposed technique and existing methods with respect to specificity, sensitivity, accuracy, MSE, and DSC metrics.



FIGURE 7: Teeth are segmented from periapical teeth images

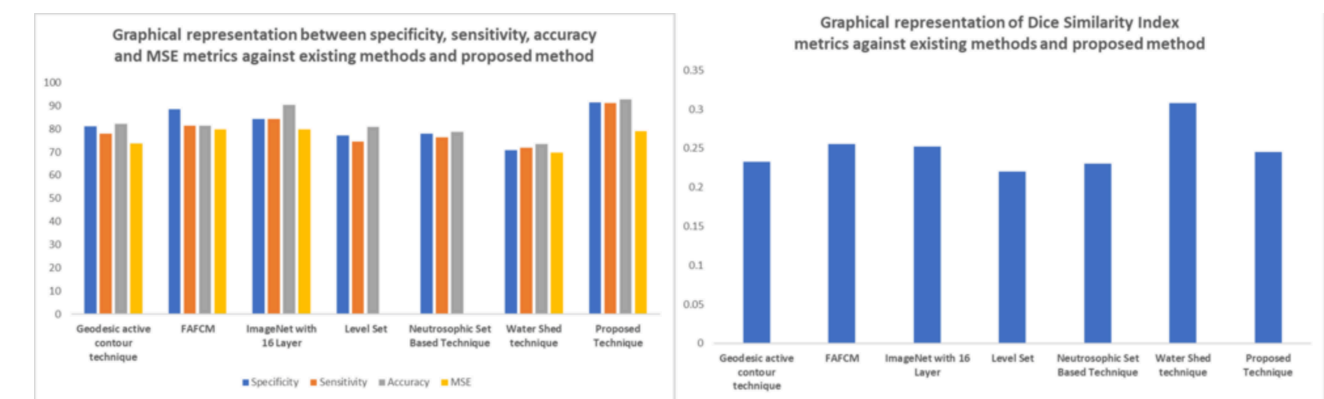


FIGURE 8: Comparison of the proposed methodology with existing methods based on a number of criteria
MSE, Mean Squared Error

Caries-affected lesion identification

This subsection explains the precise detection of caries lesions from segmented teeth. In the previous phase of this research, the teeth were segmented, and the current phase focuses on explaining and analyzing the caries lesions from the previously segmented teeth. The proposed method is applied to a publicly accessible digital dental periapical X-ray dataset [33,34]. Table 5 presents a comparative study between the proposed method and some popular existing methods. The proposed method achieves an F1-score of approximately 90-92%, indicating a good balance between sensitivity and precision in dental image segmentation.

Name of the Method	Dataset	Caries Present?/False Positives	Specificity		Sensitivity	Accuracy	Dice Similarity Coefficient	F1_Score	MSE
Geodesic active contour technique [36]	Sample_1	No		Misprediction					
	Sample_2	Yes	81.25		79.80	80.17	.19	79.67	76.45
	Sample_3	Yes	79.74		80.85	82.90	.20	78.68	72.37
	Sample_4	No							
Level set [38]	Sample_1	Yes	76.91		75.32	78.44	.24	77.12	78.26
	Sample_2	Yes	75.78		73.31	76.15	.23	76.57	73.18
	Sample_3	Yes	78.9		74.72	74.37	.21	77.53	77.52
	Sample_4	No							
ImageNet with 16 layers [39]	Sample_1	Yes	89.07		86.75	90.34	.25	89.82	86.37
	Sample_2	Yes	87.76		86.74	90.16	.19	88.17	85.19
	Sample_3	Yes	88.19		85.57	89.41	.20	88.98	88.25
	Sample_4	No							
Neutrosophic image-based technique [41]	Sample_1	Yes	90.12		89.43	91.27	.20	89.86	.79.09
	Sample_2	Yes	89.45		87.34	93.90	.219	90.12	77.78
	Sample_3	Yes	92.57		88.23	89.90	.22	89.91	80.71
	Sample_4	No							
Proposed technique	Sample_1	Yes	95.62		93.45	92.59	.18	90.18	81.83
	Sample_2	Yes	93.75		91.82	90.99	.20	89.49	80.54
	Sample_3	Yes	94.15		92.91	92.75	.19	92.12	81.19
	Sample_4	No							

TABLE 5: Comparative study between the proposed method and existing methods

MSE, Mean Squared Error

Figure 9 shows the affected and segmented caries lesion from the input dental radiographic images. Figures 9(a) and 9(c) are corresponding to input sample_1 and sample_2 in Table 5.

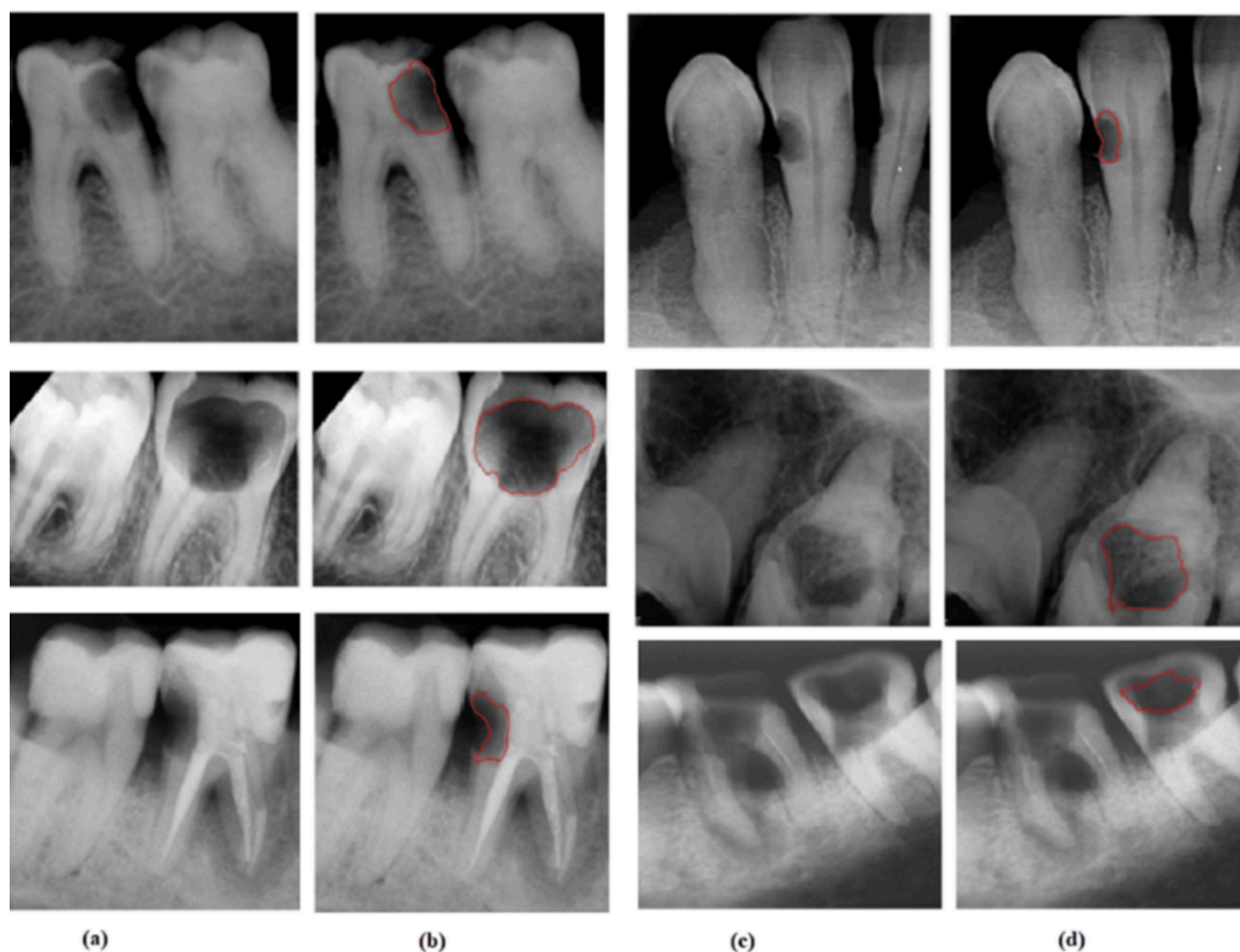


FIGURE 9: Panels (a) and (c) show the input images and (b) and (d) show the corresponding caries-affected lesion using the proposed method

Discussion

This study demonstrates the effectiveness of a three-stage method for segmenting teeth and detecting caries lesions from dental radiographic images. The method consistently achieved high segmentation accuracy across both periapical and panoramic X-rays, with DSC values exceeding 0.93, reflecting a strong alignment with expert-annotated ground truth data. However, the most notable contribution of this work lies in its exceptional computational efficiency and minimal power consumption. Unlike deep learning-based approaches, such as VGG16, which require extensive training on large datasets, the proposed method is entirely handcrafted and incorporates domain-specific knowledge from dental professionals. This customization eliminates the need for iterative training and dramatically reduces the computational burden. To evaluate energy usage, the "CodeCarbon" package was employed as an estimation tool. Although precise accuracy cannot be guaranteed, it provides useful insight into comparative power requirements. Training a VGG-16 model on 550 grayscale dental X-ray images (3,150×1,250 pixels) consumed approximately 0.93 kWh, and segmenting a single image post-training required 0.009 kWh. In stark contrast, the proposed method consumed only 0.00005 kWh per image, representing a more than 99% reduction in energy usage per segmentation task. This substantial decrease in energy consumption underscores the method's suitability for sustainable computing in medical diagnostics. As concerns around climate change and global energy consumption continue to grow, developing low-power diagnostic tools becomes increasingly essential. The energy-efficient nature of the proposed system makes it particularly valuable for deployment in low-resource or environmentally conscious clinical settings. The proposed method is designed to be

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computationally lightweight. Its performance is evaluated using both accuracy-based metrics and efficiency-oriented considerations. For comparison, we used a VGG16 model pretrained on ImageNet as a deep learning baseline. This serves as an inference-only reference for resource-intensive CNN approaches. Beyond segmentation accuracy, the pipeline excels in computational efficiency, with low energy consumption and reduced processing complexity. Occasional false positives arise in challenging cases, such as low-contrast regions or overlapping anatomical structures. Still, the results show a strong balance between accuracy and efficiency. Overall, this approach suits clinical environments with limited resources, while offering room for further improvements in robustness under tough imaging conditions.

Conclusions

This study presents an energy-efficient, three-stage method for dental caries lesion detection from radiographic images, achieving segmentation performance that is close to VGG16, but with significantly lower computational cost. By integrating domain knowledge from dental professionals directly into the segmentation process, the proposed method eliminates the need for intensive training and demonstrates substantial reductions in power consumption - an important advantage in the context of global sustainability. While the method performs reliably across various image types, its effectiveness can be affected by low-resolution inputs, occasionally leading to minor segmentation inaccuracies. To address this, future work will focus on improving image resolution and refining preprocessing strategies to enhance segmentation accuracy in challenging cases. In parallel, we aim to further optimize computational performance without compromising diagnostic quality. As the demand for sustainable AI solutions grows, energy-efficient approaches like the one proposed here not only offer practical benefits in low-resource settings but also align with broader environmental and ethical responsibilities, supporting both current clinical needs and the well-being of future generations.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Soma Datta, Pramit Ghosh, Biswajit Modak

Acquisition, analysis, or interpretation of data: Soma Datta, Biswajit Modak

Drafting of the manuscript: Soma Datta, Pramit Ghosh

Critical review of the manuscript for important intellectual content: Soma Datta, Pramit Ghosh, Biswajit Modak

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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