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Enhancing The Quality of Dental Radiographic Images: A Review on Panoramic and Periapical Radiograph Enhancement Techniques

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Abstract

Appropriate radiographic interpretation is critical for providing high-quality patient care. The radiograph's wealth of data assists dentists in prescribing the best treatment option for their patients. Dental radiographs, particularly Orthopantomograms (OPGs) and periapical radiographs taken with low radiation doses, are frequently dark, low in contrast, and noisy. Image enhancement protocols are applied to radiographs to resolve these issues. However, selecting an appropriate technique is a tedious task, especially for the purpose of disease diagnosis. This study aims to survey standard image enhancement techniques for enhancing OPG and periapical radiographs. This study also investigates the potential image enhancement protocols conducted and what are the key factors involved in selecting a protocol for a certain type of dental disease. This review categorized the radiograph enhancement algorithm into three types: contrast enhancement, frequency transforms and denoising filters, and deep learning. Extensive research has been conducted on the use of contrast enhancement and denoising filter algorithms for radiographs. The use of deep learning to enhance panoramic and periapical radiographs is still an emerging idea, and many potential results exist.

Keywords: Radiographic Enhancement; Dental Radiographs; Orthopantomograms (OPG); Panoramic Radiographs; Periapical Radiographs

Abbreviations: Orthopantomograms (OPG); Deep Neural Networks (DNN); Generative Adversarial network (GAN); Residual-in-Residual Dense Blocks (RRDBs); Discrete Wavelet Transform (DWT); Wavelet Transform (WT); Phase-Only Correlation (POC); Fourier Transform (FT); Cosine Transform (CT); Short-time Fourier Transform (STFT); Laplace Transform (LT); Wavelet Packet Transform (WPT); Homomorphic Filtering (HF); Convolutional Neural Networks (CNN); Sharp Contrast-Limited Adaptive Histogram Equalization (SCLAHE); Sharp Contrast-Limited Adaptive Histogram Equalization (SCLAHE); Contrast-Limited Adaptive Histogram Equalization (CLAHE); Global histogram equalization (HE); Adaptive histogram equalization (AHE)

Introduction

Dental radiograph, or X-ray, is a diagnostic tool commonly used in dentistry to visualize areas of the mouth. Dental radiographs are an essential component in monitoring the development of children's teeth, including the eruption of permanent teeth and the growth of jaw bones. They are also important for planning dental procedures, such as extractions, root canals, and implants, as they provide information about the location and size of roots and surrounding structures. There are several dental radiographs, including bitewing, periapical, panoramic, cephalometric, and tomography. Dental radiographs can be divided into two main types: intraoral and extraoral. Intraoral radiographs are taken inside the mouth and include periapical and bitewing radiographs. Extraoral radiographs, such as panoramic or cephalometric, are taken outside the mouth. An Orthopantomogram (OPG) or a panoramic dental image is a type of dental X-ray that captures a wide view of the upper and lower jaws and the teeth and surrounding structures [1]. It is used to diagnose various dental conditions and plan orthodontic treatment. Conversely, periapical radiographs capture a more detailed view of a single tooth or a small group of teeth [2]. These X-rays are used to diagnose specific issues with individual teeth, such as cavities, abscesses, or impacted teeth. Various sources of noise can impair image quality in panoramic and periapical radiographs. Sources of noise in radiographs include quantum, structural, electronic, pattern, data quantization, and film grain noise [3]. On the other hand, improper patient positioning can cause motion blur and additional noise in panoramic radiographs. These noise sources must be considered when interpreting radiographs for accurate diagnosis [4].

Noise in these radiographs is caused primarily by low contrast and brightness, non-alignment of images taken at different times or with different equipment, and exposure setting variability. To reduce the negative impact of noise, it is critical to use optimal parameter values, such as proper exposure settings, image alignment, and noise reduction filters. Noise in periapical and panoramic radiographs can compromise dental imaging accuracy, but it can be effectively reduced by using effective enhancement protocols and optimal parameter values [5]. Several enhancement protocols are being used to enhance the diagnostic capabilities of OPGs and periapical radiographs. These enhancement tools can be used to improve the accuracy and efficiency of dental diagnosis and treatment planning, ultimately leading to better patient outcomes. This study briefly overviews enhancement protocols for periapical and panoramic dental radiographs. The study classified the radiograph enhancement techniques into three major domains: radiograph contrast enhancement, radiograph denoising and transformation, and neural network and deep learning-based enhancement protocols as shown in Figure 1. Contrast enhancement protocols are further classified into histogram equalization-based, mathematical morphology-based, and gamma correction techniques (Figure 1).

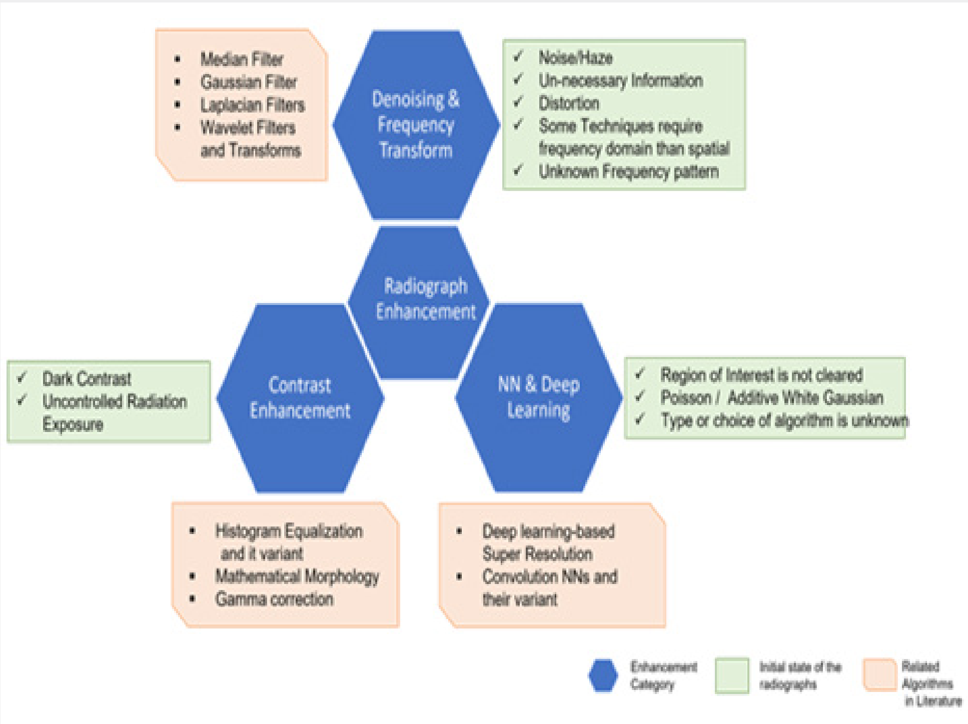

Figure 1: Summary of Radiograph Enhancement Protocols.

Image Enhancement Protocols in OPGs and Periapical Radiographs

Image enhancement protocols for OPGs and periapical radiographs typically involve adjusting the image's brightness, contrast, and color balance to improve the visibility of specific structures or lesions [6]. Some common radiograph enhancement techniques include contrast enhancement, filtering/ denoising, super-resolution, and noise reduction [7].

The key characteristics of a good radiograph enhancement algorithm are listed:

i. High Noise Reduction While Preserving the Original Edges

The radiograph enhancement algorithm should effectively reduce or remove the noise from the original radiographs while not introducing any distortion or loss of information [8]. Radiograph enhancement techniques are an important part of diagnosing dental abnormalities. To determine the extent of the abnormality's spread, the edges of the dental cavity along the jaws must be clearly defined. During the enhancement process, an algorithm must not introduce any new objects. It must maintain structural similarity with the original image while preserving all fine details. Furthermore, the boundaries of the diseased area must be precisely recognized in radiograph-guided surgeries. Most pre-processing techniques can smooth an image's edges, which is unacceptable in the case of dental images. As a result, one of the most important requirements of a good dental radiograph enhancement algorithm is preserving the edges and other finer details while removing the noise [9].

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ii. Robustness, Adaptability & Scalability

The algorithm should be robust and work well with different types of noise and different levels of intensity. Initial radiographs can have either dark or light intensity, depending upon the radiation they go through. In digital radiographs, the areas of the image exposed to more radiation will appear lighter on the final radiograph. In comparison, the images exposed to less radiation will appear lighter. The enhancement algorithm should be adaptable to different signals and noise, allowing for different parameters to be adjusted, depending on the specific application and the initial state of radiographs.

iii. Computational Efficiency

The enhancement algorithm should have a fast computation time and be able to process large amounts of data in a reasonable amount of time, requiring minimal resources.

Contrast Enhancement Techniques

Contrast enhancement is the process of improving the visibility of details in a radiograph by adjusting the intensity levels of its pixels. The goal of contrast enhancement is to make the radiographs' details more distinguishable and improve the image's overall quality [10]. This is particularly important for radiographs that are under or over-exposed, have low contrast, or are affected by noise. Several techniques for contrast enhancement include histogram equalization, adaptive histogram equalization, contrast-limited adaptive histogram equalization, gamma correction, histogram matching, and log transformation. The appropriate technique depends on the specific radiograph and application, and the results of the enhancement process should be carefully evaluated to ensure that the desired level of contrast improvement has been achieved [10].

Histogram Equalization: Histogram equalization (HE) is an image processing technique that improves image contrast by adjusting intensity levels [11]. The technique works by redistributing the intensity levels of pixels in an image so that the image's histogram is approximately flat. This results in a more balanced distribution of intensity levels and can reveal previously undiscovered details. Several HE variations techniques have been applied to OPG and periapical radiographs for clearer images and effective treatment and diagnostic tasks. These include Global histogram equalization (HE), Adaptive histogram equalization (AHE), Contrast-limited adaptive histogram equalization (CLAHE), Dual-energy histogram equalization, Automatic histogram equalization, and several other variants [11].

The global HE method applies HE to the entire radiograph and is useful for enhancing the overall contrast of an image [12]. Vinayahalingam et al. used HE to improve the visibility of details in low-contrast panoramic radiographs to classify caries in third molars [13]. HE is generally useful for improving the visibility of radiographs captured in low-light conditions. Furthermore, HE is a simple and quick image enhancement method, making it simple to implement and computationally efficient [14]. However, it should be noted that HE should be used cautiously on radiographic images because it may not be appropriate for all types of images. Radiographic images frequently have a low signal-to-noise ratio, and using HE can increase the noise, making the image more difficult to interpret [15]. Moreover, HE can increase the overall contrast of an image, making it more difficult to distinguish between subtle shades of color. In an experiment conducted by Qureshi et al. to find the consistent image enhancement evaluation metric, HE was least preferred by the survey observers [16]. An AHE technique was suggested by Peter K. Artley and James D. Young, which applies histogram equalization locally to different regions of the image instead of the whole image [17]. The technique works by dividing the image into small regions, called tiles, and performing histogram equalization on each tile separately. AHE has been effective for panoramic and peripheral radiographs because these images often have low-contrast areas, making it difficult to see small details.

A study used a variant of non-interactive sliding window adaptive histogram equalization (SWAHE) to improve contrast and radiograph quality [18]. SWAHE works by adapting the intensity levels of an entire image so that each pixel has a more even distribution of light intensity values compared to its neighbors. This makes it easier to see details in images with a wide range of brightness, darkness, or low contrast. The results showed that using SWAHE improved the ability of dentists to locate root apices in periapical examinations and detect approximal caries on bitewing radiographs with greater accuracy compared to viewing unprocessed images [18].

However, SWAHE can be computationally intensive because of the number of blocks that need to be processed and the calculations required for each block [19]. For example, the histogram of each block must be calculated and equalized, which involves counting the number of pixels in each intensity level, normalizing the histogram, and computing the cumulative distribution function. In addition, because the blocks overlap, the same pixels may be processed multiple times, which can increase the computational complexity. Furthermore, the algorithm may require a large amount of memory to store the intermediate results for each block [19]. Another enhancement method is the CLAHE, which is similar to HE, but it limits the amount of contrast enhancement to prevent over-saturation of the image. CLAHE modifies the image's brightness intensity by expanding brightness values between dark and bright areas [20]. Initially, this method of local contrast enhancement was created to improve medical images. The initial research on CLAHE was done on dense mammograms and effectively improved the simulated speculations [21].

A study examines the effect of HE and CLAHE on image quality and fractal dimensions of digital periapical radiographs [22]. Sixty digital periapical radiographs were used for the study, and

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the radiographs were separated into three groups: the first group was enhanced with HE, the second group was enhanced with CLAHE, and the third group was left untreated. Two observers investigated the image quality and fractal dimensions using the Wilcoxon signed-rank test and the Kruskal-Wallis test. According to the results, both image-enhancing strategies enhanced the image quality and fractal dimensions of digital periapical radiographs. However, the CLAHE method was found to be more effective than the HE method at enhancing image quality and fractal dimensions [22]. A new technique uses image processing to automate the localization of the inferior alveolar nerve canal (IAC) in maxillofacial regions of cone beam computed tomography X-ray images. The technique enhances the image using intensity mapping and contrast limited AHE, then segments the lower jaw into two portions and extracts edge points to identify the IAC [23]. Another study tested a variation of CLAHE called sharp contrast-limited adaptive histogram equalization (SCLAHE) on ten intra-oral periapical x-ray images and found that it provided better diagnostic ability for dentists [24]. The study was conducted on four upper jaw molars and six lower jaw molars to determine whether this strategy improves diagnostic accuracy. However, the SCALHE enhancement process can amplify noise present in an image, resulting in a noisier image. Moreover, it is a computationally intensive process, which can be slow for large images.

Nevertheless, CLAHE radiograph enhancement is linked to the strong foreground and background contrast, which improves the appearance of the primary mass at the expense of creating tiny but misleading intensity inhomogeneities in the background [25]. CLAHE and HE, on the other hand, reduce trabecular bone structure detection and FD values in periapical images [22]. Thus, several studies suggested the use of HE and CLAHE algorithms in combination with other algorithms for effective radiograph enhancement [26]. Chen et al. used a combination of HE and flat-field correction to assign pixel values in dental radiographs for missing teeth and restoration detection [27] (Table 1).

Table 1: Summary of Radiograph Contrast Enhancement Protocols

Technique Name	Application Area	Publications/ Research Papers	Merits	Demerits
Histogram Global Histogram Equal-ization	- Classification for carries in third morals - Differentiating the dental component from the noise component	Vinayahalingam et al. [13] Arunkumar et al. [62]	It is useful on Images with non-uniform illumination or regions with varying contrast.	- Over Enhancement - Introduction of artifacts
SWAHE	- root apices - approximal caries	Sund & Møystad [18]	For periapical examinations, a twin view raised the image quality by 52% compared to a single view.	Computationally intensive because of the number of blocks that need to be processed. Wei & Tao [19]
CLAHE and its variant, SCLAHE	Detection of upper and the lower jaw morals	Mehdizadeh et al. [22] Ahmed et al., [24]	Enhanced fractal dimensions of digital radiographs	- Computationally expensive - Reduced trabecular bone structure detection and FD values in periapical images Mehdizadeh et al. [22]
HE with flat-field correction	- Missing teeth - Restoration detection	Chen et al., [27]	The flat-field correction ensures that the image has a more uniform background, and the histogram equalization helps to bring out details in the radiograph	Complicated implementa-tion where the radiographs have non-uniform illumi-nation
Mathematical Morphology	- To extract the relevant struc-tures in the radiograph - Teeth Segmentation. - Fractal dimension analysis	Román et al. [30] Said et al. [29] Yu et al. [31]	- Improved visualization - Enhance the contrast and visibility of morphological features	- Computational complexity Cuisenaire [32] - Limited interpretability of the results
Gamma Correction	For the automatic segmenta-tion of dental X-ray images	Asadi Amiri, Moudi [33] Versteeg et al. [8]	- Standardization - Improves image visibility	- Complexity - Distortion

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HE is a widely used technique for improving the visibility of details in images. However, it also has some limitations that can negatively impact the quality of the enhanced image. One of these limitations is over-enhancement, which can result in unnatural and unrealistic contrasts in certain regions of an image. Another issue is noise amplification, which occurs when the enhancement process amplifies any existing noise in an image, making it noisier. Additionally, HE can lead to loss of information in an image as the adjustment of intensity levels can result in deleting some information. Lastly, HE is a global enhancement technique that enhances the entire image equally. This may not be appropriate for images with multiple regions with different lighting conditions, as it can result in an uneven enhancement. To address these limitations, it is important to carefully evaluate the results of HE and choose an appropriate enhancement technique that best suits the specific image and application, like the AHE. The hybrid methods combine different image enhancement techniques to address the limitations of histogram equalization and improve the overall quality of the enhanced image. It is essential to utilize histogram equalization in conjunction with other image processing techniques and to interpret the results considering the clinical presentation of the patient.

Mathematical Morphology: Mathematical morphology is a technique used in dental radiograph processing for extracting and enhancing morphological features in images. The use of mathematical morphology to enhance morphological features in medical images is widely recognized in the medical imaging field to improve the visibility of crucial features, such as shapes, textures, and structures, which play a crucial role in diagnosis and treatment planning. The morphological operations used in this technique include dilation, erosion, opening, and closing, which can be applied to a radiograph to enhance or remove specific features [28]. A study by Said et al. investigates the application of mathematical morphology to tackle the challenge of teeth segmentation in medical images [29]. The authors also put forward a novel grayscale contrast stretching transformation aimed at enhancing the performance of this technique. This innovative approach demonstrates remarkable results in both bitewing and periapical dental radiographic images and boasts the lowest failure rate among all the approaches studied [29].

Another study extends the use of mathematical morphology for enhancing panoramic radiograph images [30]. The method proposed in the paper is based on the use of mathematical morphology operations to extract the relevant structures in the radiograph at multiple scales. The authors use the mathematical morphology operations of dilation and erosion at different scales to extract the desired structures in the image. They then combine these structures to produce an enhanced final image. The authors evaluate the performance of their method using a dataset of OPG images. They compare their method to other existing methods for image enhancement, such as HE and the anisotropic diffusion filter. They show that their method produces improved results in terms of image quality and visibility of structures [30].

To extract the trabecular pattern and assess changes in reactive bone, a research study employed mathematical morphology and box-counting techniques [31]. The central conclusion of this research paper is that the fractal dimension of reactive bone shows a substantial reduction following successful root canal treatment. The study revealed significant alterations in the fractal dimension six months after the root canal treatment, suggesting a decline in the fractal dimension in areas previously characterized by dense reactive bone formation caused by necrotic pulps or periapical lesions resulting from endodontic procedures such as root canal treatment. This method holds potential as a quantitative tool for evaluating the bony structures of the jaw before and after dental procedures like root canal treatment. Mathematical morphology can lead to improved visualization of important structures and patterns in these images, making it easier to detect and analyze them.

Furthermore, it can be used to perform automated image analysis, reducing the time and effort required for manual analysis and providing objective measurements of morphological features. This reduces the subjectivity and variability associated with manual measurements. It can also improve diagnosis accuracy by providing a clearer and more detailed view of morphological features in medical images interpretability [32]. However, there are also some limitations to using mathematical morphology, including computational complexity, noise sensitivity, the potential for over- or under-enhancement of morphological features, and limited interpretability [32]. To summarize, mathematical morphology can provide valuable insights into morphological features in medical images, but it is important to consider its limitations and choose the appropriate morphological operations to ensure accurate and meaningful results.

Gamma Correction: The use of gamma correction enhances the quality of images by adjusting their brightness and contrast levels. This method involves manipulating the mid-tones of an image, either by making them brighter or darker, to improve its visibility and clarity, particularly on images with limited dynamic range. Gamma correction can be applied manually or through automated algorithms, offering greater flexibility and improved results. A research study revolved around the utilization of gamma correction for enhancing panoramic images. This method involves modifying the brightness and contrast of an image to improve its visibility and clarity, particularly on radiographs. By implementing gamma correction, the accuracy of positioning can be improved, as it provides clearer images with sufficient diagnostic information for the maxilla sinusoid region, resulting in decreased exposure to radiation for patients [33].

Another study utilized gamma correction for image enhancement for the automatic segmentation of dental X-ray images. The training procedure involves several stages, including

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data augmentation, pre-processing with CLAHE and gamma adjustment, and training using the U-Net architecture. During the testing process, the image undergoes pre-processing, prediction, and the removal of small background areas [34]. The gamma correction method aims to improve the visibility of images, especially in low-light conditions, by making them clearer and more defined. Additionally, gamma correction helps to standardize the display of images across different devices, making it easier to view images accurately on different screens. Another advantage of gamma correction is that it can enhance the representation of colors in an image, making them appear more accurate and vibrant. Despite its benefits, there are also some drawbacks to using gamma correction. The process can be complex and time-consuming, particularly for large images. Additionally, over-correction can lead to the loss of fine details in an image, and if not performed correctly, gamma correction can result in a distorted image that appears unnatural. In conclusion, while gamma correction can be useful for improving the appearance of an image, it should be applied carefully to avoid negative consequences.

Radiograph Denoising and Transform:

Radiograph Denoising: The images radiographs produce can sometimes be degraded by random noise, making it difficult to accurately diagnose dental conditions. Consequently, there is a growing interest in enhancing the quality of dental radiographs through denoising. Denoising is a process that removes or reduces random noise in an image. There are various methods for denoising dental radiographs, including wavelet denoising, total variation denoising, and deep learning-based denoising. The choice of denoising method depends on the specific needs of the application and the trade-off between noise reduction and preservation of important details. A Gaussian high-pass filter is used to preprocess the image data in a study. The X-ray image is then divided into several individual tooth sample images using iterative thresholding. For training, the image database's collection of individual tooth images is used as input into the convolutional neural networks (CNN) migration learning model [35]. Before starting the feature extraction process, it is important to clean up the images by removing noise and preserving edge information. This is achieved through the use of Gaussian filters that prevent the smoothing of edges [36].

The median adaptive filter is another widely used method for removing impulsive noise in dental radiographs [6]. The procedure for segmenting individual teeth has been proposed for an effective distinction of various features, such as caries lesions, fractures of dental structures, including teeth and supporting alveolar structure, and diseases, such as periodontitis, among others. The first step involves preprocessing through median filtering, followed by K-means clustering with morphological operations to differentiate tooth structures from the dental X-ray images [37].

The median filter has several advantages, including robustness against impulsive noise, a lack of requirement for prior knowledge of noise statistics, and the ability to preserve edges. However, it also has some limitations, including slower computation time, the potential for blurring, and the risk of removing important details [6]. The preprocessing of images involves identifying the relevant area (ROI) and applying image enhancement techniques. A bounding box is placed around the first and second permanent mandibular premolars in panoramic dental radiographs, with the object centered within the image. The image's intensity is then adjusted, and a median filter is applied to improve the quality of the image. This step helps to bring out the important features of the object while minimizing background noise. The median filter removes any sudden noise spikes while preserving the edges of the object, and a 7 x 7 kernel filter is applied for further processing [38]. Wavelet denoising is also a well-established denoising method for removing noise from digital images. It is based on the wavelet transform, which decomposes an image into different frequency sub-bands. The method then applies a threshold to the wavelet coefficients in each sub-band, which reduces the magnitude of the noise while preserving the important details.

A paper presents a promising solution for enhancing X-ray images to detect dental caries. The approach is based on locating the lesion using CLAHE, followed by a morphological top and bottom hat operation. Homomorphic filtering (HF) is then applied to eliminate uneven luminance distribution and reduce noise. The HF is implemented using wavelet packet transform (WPT), and the wavelet shrinkage decomposition and threshold of the wavelet coefficients are determined adaptively [39]. The technique can easily be applied to OPG and periapical radiographs for effective image enhancement. The wavelet filters are proven to be an effective method for removing noise from the radiographs. However, the selection of the appropriate wavelet function is crucial for the effectiveness of the denoising process [40]. If an incorrect function is chosen, it may result in the preservation of noise or the removal of important details in the image. Wavelet denoising can also result in over-denoising, which results in too much noise removal from the image, leading to a loss of important details and degradation of radiographic quality [41].

In image processing, the frost filter is a denoising, non-linear filter that is especially effective at removing speckle noise from medical images, such as ultrasound and X-ray images. To analyze the image and separate signal from noise, the frost filter employs a multi-scale approach. It computes a local mean and standard deviation for each pixel before replacing it with the weighted average of the surrounding pixels if the pixel value deviates from the local mean by more than a certain threshold. The frost filter effectively reduces speckle noise while preserving the image's edges and fine details. As a result, it is a popular option for denoising medical images and improving image quality for

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diagnostic purposes [42]. In dental radiography, one of the main sources of noise is the X-ray quantum noise, which is influenced by the X-ray dose received by the patient and the characteristics of the image intensifier. Another source is the electronic noise from the TV camera, which includes noise from the pre-amplifier and the camera tube and can produce a speckled appearance in the image. Hence, another research study used the frost filter to remove noise from the digital periapical images [43] This method aids in the accurate localization and detection of lesion boundaries, providing improved results for bone repositioning following surgery for periapical lesions.

The wiener filter is a commonly used method for noise removal in dental radiography. A method is presented for identifying people based on the shapes and appearances of their teeth using edge detection, pixel value counting, and feature extraction. This method automatically detects important features to identify a person. The wiener filter is used to reduce noise and provide a smooth image [44]. It offers several advantages, including optimal signal-to-noise ratio, adaptive filtering, and computational efficiency [45]. However, the filter requires knowledge of noise statistics, and over-aggressive noise suppression can lead to blurring or over-smoothing of the image. The Laplacian filter is an important component of the diagnostic system for detecting dental caries in digital radiographs. This filter highlights the edges of the image, which are crucial for accurately identifying areas of caries in teeth. The diagnostic system consists of several components, including Laplacian filtering, an adaptive threshold based on the window size, morphological operations, statistical feature extraction, and a back-propagation neural network. The Laplacian filter calculates the second derivative of the image intensity values. This provides information about how quickly the intensity changes over a certain area of the image, which is useful for identifying boundaries between different objects in the image. For example, the boundary between a healthy tooth and a carious area will have a higher intensity change rate than other areas of the image. The latter determines whether a tooth surface is normal or has dental caries.

In a study, the system was trained using 105 intra-oral digital radiography images, which a dentist annotated to indicate the presence of caries. The training was conducted using an artificial neural network with 10-fold cross-validation. The performance of the diagnostic algorithm was evaluated and compared against other conventional methods [46] (Table 2).

Table 2: Summary of Radiograph Denoising/ Frequency Transform Protocols

Technique Name	Application Area	Publications/ Research Papers	Merits	Demerits
Median / (Adaptive Median)	- Caries lesions, - Fractures of dental structures - Detection of Periodontitis	Al-Beiruti, Jeiad [51] Singh, Sebgal [37] Mohammad et al. [64]	- Robust against impulsive noise - No prior knowledge of noise statistics required	- Slower computation time -Introduce blurring
Wavelet	- Caries detection - Precise diagnostic of dental lesions	El-Dahshan [40] Al-Beiruti, Jeiad [51]		- Concerns regarding the selection of wavelet function s et al. [41]
Frost filter	- Accurate localization -detection of lesion boundaries	Vasavi et al. [43] Hoover et al. [42]	- Providing improved results for bone repositioning -Preservation of details	- Sensitivity to parameter selection -Increase computational complexity making it less suitable for real-time applications
Gaussian filter	Caries detection	Majanga, Viriri [36] Chuo et al. [35]		
Wiener	Identifying shapes and appearances of the teeth	Rabbani et al. [44]	Optimal signal-to-noise ratio Kumar & Nachamai [45] Computationally efficient	- Assumes known noise statistics -Lead to the blurring of the image
Laplacian Filter	- Dental Caries detection -Tooth edges detection	Geetha et al. [46]	High-Frequency Component Enhancement Computational Efficiency	- Implementation Complexity -Amplification of Speckle Noise

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Radiograph Transforms: Radiograph transformation is the process of manipulating and adjusting the radiographic image to improve its quality or make it more useful for a particular purpose. This process involves various mathematical techniques and algorithms that can transform the image from one coordinate system to another or change its format. The transformation can be performed to correct distortions, enhance details, remove noise, adjust the image to meet specific requirements, or convert it to a different format. The OPG and periapical radiograph transform methods available in the literature are classified into two main categories: Enhancement techniques for the spatial domains and frequency domain techniques [47].

Spatial domain approaches directly manipulate image pixel values, either RGB or greyscale. The pixel values are manipulated to accomplish the desired improvement. In frequency domain methods, the image is converted to a frequency domain, and a radiograph transform method is applied to the converted image. Converting an image into the frequency domain, also known as the Fourier transform, allows the image to be represented in terms of its frequency components [48]. This can be useful for various image processing, such as filtering, enhancement, and compression. One of the main advantages of working in the frequency domain is that it allows for more precise control over specific frequency components in an image. For example, by analyzing the frequency content of an image, it is possible to identify which frequency components are responsible for certain features, such as edges or textures. This can selectively enhance or suppress specific features in the image. In addition, many image processing tasks, such as filtering, can be performed more efficiently in the frequency domain. For example, convolution in the spatial domain requires many multiplications and additions, whereas convolution in the frequency domain can be performed using simple, complex multiplications. It is important to note that converting an image into the frequency domain can be a lossy process, and the result must be converted back to the spatial domain to be visualized.

Different methods exist for transforming an image into the frequency domain, including the Fourier Transform (FT), Cosine Transform (CT), Wavelet Transform (WT), Short-time Fourier Transform (STFT), and Laplace Transform (LT). FT is a mathematical representation of a radiograph in the frequency domain. It is widely used in standard image processing and signal processing applications. A research study proposed an efficient dental radiograph registration algorithm using Phase-Only Correlation (POC). POC uses the phase components in 2D discrete FT of dental radiographs to achieve robust image registration and recognition [49]. The most common method for performing the Fourier Transform is the Fast Fourier Transform (FFT), which is an efficient algorithm for computing the discrete FT of a signal or image. A research study presents an algorithm for the automatic detection of endodontic files in digital dental radiographs and uses FFT to convert images into frequency spectra and detect frequencies. These frequencies are then used to design a pre-segmentation filter programmed using the software. Performance evaluation revealed that this software could segment the endodontic files with greater accuracy [50]. The Wavelet Transform (WT) decomposes an image into different frequency components, or wavelets, by filtering the image with a series of low-pass and high-pass filters. The Discrete Wavelet Transform (DWT) is a specific method of WT that is particularly useful for image compression and denoising.

The algorithm involves image enhancement using a hybrid filtration of noise reduction via the adaptive median filter and discrete wavelet transform and contrast enhancement via mathematic morphology and CLAHE [51]. The segmentation of the images is then performed using Otsu's thresholding and canny filter, followed by extracting texture features such as First-order statistics, gray level co-occurrence matrix, and Gray Level Run Length Matrix. This process aims to obtain a precise diagnosis of dental lesions and improve the accuracy of the OPG image quality for early detection. Denoising and transformation techniques are typically included in the preprocessing stage when it comes to enhancing radiographs. However, determining which technique should be applied first is not straightforward and requires a thorough analysis before implementation. It is interesting to note that whether denoising should be performed before or after the transformation of an image into a radiograph can depend on the specific application and the type of noise present in the image. In general, it is recommended to perform denoising before the transformation if the noise present in the image is additive, such as Gaussian noise. This is because additive noise can be modeled and filtered using techniques such as filtering, wavelet transform, or deep learning methods.

However, if the noise present in the image is multiplicative, such as speckle noise, it is recommended to perform denoising after the transformation [52]. This is because multiplicative noise can be more challenging to model and filter out, but it can be reduced by taking the square root or logarithm of the image after the transformation. In practice, it is common to perform denoising before and after the transformation to achieve the best results. For example, a denoising filter can be applied before the transformation to reduce additive noise, and then a denoising filter can be applied after the transformation to reduce multiplicative noise. It's worth noting that the best approach will depend on the specific characteristics of the image and the noise present [53].

Neural Network and Deep Learning-based Radiograph Enhancement Protocols:

Deep learning-based dental radiograph enhancement is a method of using deep learning algorithms to improve the quality of dental radiographs. This technique involves training deep neural networks on a large dataset of high-quality dental radiographs and using the learned features to enhance new, low-quality radiographs. Deep learning-based dental radiograph enhancement works by learning a mapping from low-quality radiographs to high-quality radiographs. This mapping can be represented by a deep neural network, which is trained on a large dataset of example radiograph pairs. During training, the network learns to extract high-level features from the input radiograph and then uses these features to generate a high-quality output radiograph. Once trained, the network can enhance new radiographs by feeding them through the network and using the output as the enhanced radiograph. Despite extensive research on the use of neural network-based algorithms to improve general medical radiographs, the use of deep learning to enhance panoramic and periapical radiographs is still a novel idea. Thus, this section discusses the use of these enhancing protocols in medical radiographs in general than specific to panoramic and periapical radiographs.

Shi et al. proposed a residual learning-based MRI approach [54]. Similarly, Zeng et al. developed a convolutional neural network for super-resolution reconstructions of magnetic resonance images, which was effective for multi-contrast images [55] The super-resolution technique involves using algorithms that can predict high-resolution images from low-resolution images. These algorithms use advanced mathematical and computational techniques to analyze and enhance the details in the image. They can improve the accuracy and reliability of diagnostic results by enhancing the visibility of subtle changes and abnormalities in the image. Zhang and An. proposed a bicubic interpolation solution followed by convolution layers deep-learning solution, which was then improved by transfer learning [56]. They used this method on various medical images, including MRI, mammography, and angiography. SMORE, a deep-learning approach for improving the visualization of brain lesions in fluid-attenuated inversion recovery images, was introduced by Zhao et al. [57]. Oral radiographs have also benefited from deep learning-based resolution improvement techniques. Hatvani et al. proposed a tensor-factorization-based method for improving dental cone-beam computerized tomography, resulting in a magnification increase of two times [58]. SRCNN [59] and SRGAN [60] are two impressive deep-learning methods for super-resolution in medical imaging, with the best results in the literature for benchmark datasets.

A recent study presented a new technique to enhance the quality of panoramic images taken by fisheye lens cameras. A new "Panoramic-Highend" dataset was introduced as the first real-world panoramic image dataset. The authors designed a compact network incorporating a multi-frequency structure, compressed Residual-in-Residual Dense Blocks (RRDBs), and convolution layers. This network is based on a generative adversarial network (GAN). The results of the experiments indicated that this method outperforms other state-of-the-art deep neural networks (DNN) methods in both no-reference and full-reference evaluations, while also providing faster processing speed [61-64] (Table 3).

Table 3: Summary of Deep Learning-based radiograph enhancement Protocols.

Deep Learning NN's and their variants	Application	Merits	Publications
CNN	for super-resolution reconstructions of magnetic resonance images	Effective for both single and multi-contrast images	Zeng et al. [55]
CNN-based residual learning	Enhancement of MRI images	Less computational complexity as compared to standard CNN	Dong et al. [54]
CNN with transfer learning	Various medical images, including MRI, mammography, and angiography	Resource and time efficient	Zhang & An. [56]
SMORE (a deep learning approach)	Visualization of brain lesions		Zhao et al. [57]
Tensor-factorization-based method	Oral radiograph resolution improvement	Two times magnification increase	Hatvani et al. [58]
SRCNN & SRGAN	Super-resolution in medical imaging	Best results in the literature for benchmark datasets	Ledig et al. [59] Dong et al. [60]
Compressed Residual-in-Residual Dense Blocks (RRDBs)	Panoramic images	Faster processing speed	Zhang et al. [61]

Conclusion

In this review, OPG and periapical radiographs were categorized into three domains of enhancement techniques: Frequency Transforms/ Denoising, Contrast Enhancement, and Neural Network-based Deep learning techniques. Image enhancement aims to improve the visibility and quality of these radiographs, which are initially noisy and have low contrast. The

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choice of enhancement technique depends on the quality of the original image and the specific diagnostic task. It is noteworthy that, while histogram equalization can improve visibility, it can also increase noise levels and create a false sense of greater detail. Thus, its effectiveness must be evaluated on a case-by-case basis and based on the characteristics of the image and the diagnostic task. Additionally, too much enhancement can lead to distortions and misinterpretation; hence, the application of HE can aid practitioners in making more accurate diagnoses. However, applying the pre-processing step cautiously is crucial to avoid the loss of diagnostic information. Finally, it is essential to use contrast enhancement in conjunction with other image processing techniques, such as noise reduction, to ensure that the final image is of high quality.

The results of the contrast enhancement process must be thoroughly evaluated to ensure that the desired level of contrast improvement has been achieved without compromising the information content of the image. To further reduce unwanted background noise in radiograph images, denoising techniques are a useful domain area to explore. To analyze radiographs efficiently, most denoising and contrast enhancement methods require that they be converted from one spatial domain to another. The choice of whether to perform denoising before or after the transformation of an image into a radiograph can vary depending on the type of noise present in the image and the specific application. It is important to consider the characteristics of the image and the noise to determine the best approach to denoising. Regardless of the approach chosen, it is common to apply denoising both before and after the transformation to achieve the best results. Ultimately, the goal of denoising is to enhance the quality of radiographs for accurate diagnosis and treatment, and developing effective denoising techniques is critical in achieving this goal. Overall, deep learning-based dental radiograph enhancement has shown promising results and has the potential to provide more accurate and clearer images for dental professionals, ultimately leading to improved diagnosis and treatment planning.

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