International Journal of Innovative Engineering Applications

Journal homepage: https://dergipark.org.tr/ijiea

APPLICATION OF PANORAMIC DENTAL X-RAY IMAGES DENOISING

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Abstract

Original scientific paper

Dental X-ray imaging helps dentists detect many problems such as caries, cysts, and jaw structure problems. Clinical diagnosis and preventive examinations of dental structures play an important role by providing a comprehensive imaging evaluation with panoramic x-rays for dentists. Therefore, researchers primarily use image processing methods to analyze and improve a dental X-ray image and increase its contribution to the diagnostic time. Image segmentation, classification, threshold-based analysis, artificial neural networks, and frequency-based methods are the most widely used image processing techniques to analyze medical images and assist in the development of computer aided medical diagnosis systems. In this study, images were analyzed in terms of noise removal by using convolutional neural networks and binary and wavelet filters to improve the images that were distorted and lost their clarity as a result of noise caused by various reasons during shooting. The performances of these methods were compared, and it was seen that successful results were obtained in different noise types by using convolutional neural networks.

Keywords: *Convolutional neural network, denoising, panoramic radiograph, wavelet.*

PANORAMİK DİŞ X-RAY GÖRÜNTÜLERİNİN GÜRÜLTÜ GİDERİLMESİ UYGULAMASI

Özet

Orijinal bilimsel makale

Dental röntgen görüntülemesi, diş hekimlerinin çürük, kist ve çene yapısı sorunları gibi birçok sorunu tespit etmesine yardımcı olur. Diş hekimleri için panoramik röntgenler ile kapsamlı bir görüntüleme değerlendirmesi sağlayarak diş yapılarının klinik teşhisi ve önleyici muayeneleri önemli bir rol oynamaktadırlar. Bu sebeple, araştırmacılar öncelikle bir dental röntgen görüntüsünü analiz etmek, iyileştirmek ve teşhis süresine katkısını artırmak için görüntü işleme yöntemlerini kullanırlar. Görüntü bölütleme, sınıflandırma, eşik tabanlı analiz, yapay sinir ağları, frekans tabanlı yöntemler, tıbbi görüntüleri analiz etmek ve bilgisayar destekli tıbbi teşhis sistemlerinin geliştirilmesine yardımcı olmak için en yaygın kullanılan görüntü işleme teknikleridir. Bu çalışmada, çekim sırasında çeşitli nedenlerle oluşan gürültünün sonucunda bozulan ve netliğini kaybeden görüntülerin iyileştirilmesi için evrişimsel sinir ağları, biliteral ve dalgacık filtreleri kullanılarak görüntüler gürültü giderme açısından analiz edilmiştir. Bu yöntemlerin performansları karşılaştırılmış olup evrişimsel sinir ağları kullanılarak farklı gürültü türlerinde başarılı sonuçlar elde edildiği görülmüştür.

Anahtar Kelimeler: *Evrişimsel sinir ağları, gürültü giderme, panoramik röntgen, dalgacık.*

1 Introduction

Medical images x-ray, computed tomography, magnetic resonance can be obtained by various methods X-ray images are used in many medical areas. Dental x-rays are one of them. Thanks to the x-ray and imaging applications performed within the scope of dentistry services, diagnosis and treatment processes can be carried out effectively. Dental radiology and imaging play a role in diagnosing oral and dental health problems and creating a treatment plan. Thus, it increases the success of the dentists and the satisfaction of the patients directly in the follow-up of the treatment processes. In addition to these, X-ray imaging is generally preferred because it is a low-cost method [1].

Panoramic x-ray is an important factor in the definitive diagnosis of many dental applications that cannot be detected during physical examination, such as determining the position of the impacted tooth, diagnosis of jawbone fractures, implant planning, root canal treatment. Taking advantage of the developing technological opportunities contributes to better results from the treatments. Panoramic

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Received 22 June 2022; Received in revised form 03 November 2022; Accepted 06 March 2023

 Doi: https://doi.org/10.46460/ijiea.1134105

x-ray application, which enables the visualization of pathological formations in the teeth, jaw bones, and jaw bones in a single film, is an important application that is frequently used to obtain effective results in dental treatments. The physician's imaging of all the details helps to carry out the correct diagnosis and treatment processes. Therefore, after the first examination of the patient, it is drawn to determine the treatment way.

X-rays were used as the material of many studies to increase the quality of images, classify or cluster certain features, and identification applications. Denoising operation for biomedical images is an important and challenging task as it requires the elimination of non-image components while preserving some details of diagnostic information, which can be done in many different ways [2]. The body region where medical imaging takes place and the image characteristics of this region affect the noise generation and noise removal success[3].

In recent studies, two types of image noise removal methods are used, these are traditional algorithms and neural network-based deep learning methods. Methods based on wavelet transform are among the traditional methods. The main advantages of the wavelet decomposition and reconstruction method are its simple algorithm and short processing time due to fast computation. However, in the removal of some types of noise, such as white noise, these methods yield not very good performances from this method [4].

In this study, noise removal processes were applied using wavelet and bilateral filters, especially convolutional neural networks (CNN), which can bring new approaches to noise removal and has a good performance.

The most important criterion in determining the model architecture is to determine the appropriate depth for better performance. The depth of the model should be decided depending on the effective patch size and noise level in the image. Usually, high noise level image noise removal task requires large effective patch size. The DeepCNN model proposed here now learns to predict the image and this process is aimed at distinguishing the main image and the noise according to the information it has learned[5].

With the development of deep learning, some methods have outperformed traditional image analysis and computer aided diagnostic technologies. It is seen in the studies that deep learning methods provide high performance in removing ambiguous noise types thanks to their higher level of feature representation capabilities than traditional methods. Deep convolutional neural networks, such as deep convolutional neural networks, have achieved great success in the field of image noise removal. DnCNN network is frequently used in the literature to remove Gaussian noise [6].

Deep convolutional neural networks have been popular in medical research in recent years due to their impressive results in detection, prediction, and classification. Analysis of panoramic dental radiographs helps professionals observe problems in areas where vision cannot be clear or in hard-to-reach areas. at the same time, poor image quality or fatigue can lead to deviations in the accuracy of the diagnosis, which can ultimately hinder treatment. For this reason, as in all other medical imaging fields, the use of panoramic X-Ray images, which can help medical personnel make decisions regarding the correct diagnosis, is one of the most frequently applied methods in the dental field [7].

Wang et al., 3 different methods based on deep learning were used for noise removal and their performances were compared. It has been shown that deep learning-based methods can be used for noise removal both purely and hybridly [8].

Wavelet-based methods decompose the image into many sub-bands as low and high frequency components to form a filter bank using perpendicular wavelet coefficients and perform a thresholding operation on the coefficients [9], [10]. Many thresholds value estimation and thresholding methods have been proposed in this field. Thresholding is a method that accepts the noise component of the simple nonlinear wavelet-based transform coefficients and eliminates them as noise components. If the coefficients are less than the estimated threshold value, they take the value to zero, if they are larger, they are either kept as they are or changed. This process is called hard or soft thresholding, depending on how it is applied.

In spatial domain filtering from traditional methods, the image is separated into frames and each frame is filtered one by one. It is a kind of spatial domain filtering method in bilateral filtering. Biliteral filters are used to prevent image deterioration and they are non-linear edge-protecting and noise-reducing, smoothing filters [11].

Therefore, the aim of the present study is to evaluate the application of four noise reduction algorithms to 4 different noises for dental panoramic x-ray images and to perform a comparative analysis of the algorithms' performance.

Section II describes the materials and methods in other parts of this article. Section III includes the experimental procedure, the relevant results, and considerations of the results. The final general analysis of the article was made in section IV.

2 Material and Methods

2.1 Material

Images were taken from Dentanest Plus Dental Clinic in Ankara. The images used in this study include images taken for periodic controls of patients in the 0-12 age group. Images are obtained from Morita brand 2D/3D Imaging model device. All the methods are applied for 30 test images. Images size is 1536x2871x3.The dataset hasn’t been used in an academic or scientific study before.

2.2 Methods

2.2.1 Convolution Neural Networks (CNN)

Convolutional neural networks entered the literature for the first time with the work of LeCun et al. [12]. It is frequently preferred for operations where feature extraction cannot be done manually in signal image and video based applications [13]. In literature, generally CNN is used for removing for gaussian [14]–[16] and salt&pepper [17]–[20] noise. In particular, it is seen that the studies on the elimination of gaussian noise are in the majority [11]. CNN is one of the deep learning methods that stand out with their speed and accuracy. CNN have been used to solve problems encountered in many fields such as image processing and signal processing in recent years. Denoising convolutional neural network (DnCNN) is a method prepared to reduce noise in images and provide a high-performance solution. DnCNN has been preferred in many applications because it is a method that increases the processing performance by reducing the amount of data. However, it should be noted that CNN networks can also increase the amount of error as the depth of the network increases. [11]. Although DnCNN is used in the denoising processes of many different medical images, there are limited studies for panoramic x-rays.

CNNs like traditional neural networks at each layer. CNNs are used in many applications, but pattern recognition is one of the prominent ones [21].

The convolution layer includes the stages of convolution, activation function (relu) and pooling and provides extraction of low-dimensional features from high-dimensional data.

Therefore, basic layers of CNN architecture consists of three layer; these are convolutional layer, pooling layer and fully-connected layer.

Multiple convolution and pooling layers can be positioned in succession Next, several fully connected layers are lined up. With a fully-connected layer, it receives three-dimensional input by reducing it to one dimension and a class label is obtained.The softmax layer at the end of the solution architecture of multi-class classification problems performs the calculation of the probability distribution of the output classes. The sequential coupling depth of the convolutional layer varies, specific to the problem. The classification layer, on the other hand, provides the matching of low-dimensional features and categories and generally has a fully connected neural network architecture. The convolution operation (Eq. (1)) in the first stage of the convolution layer allows the image to be filtered with a mask. It aims to obtain images of the same size as the original image, such as horizontal edges, vertical edges, angular edges, softened image, sharpened image as a result of convolution [22]

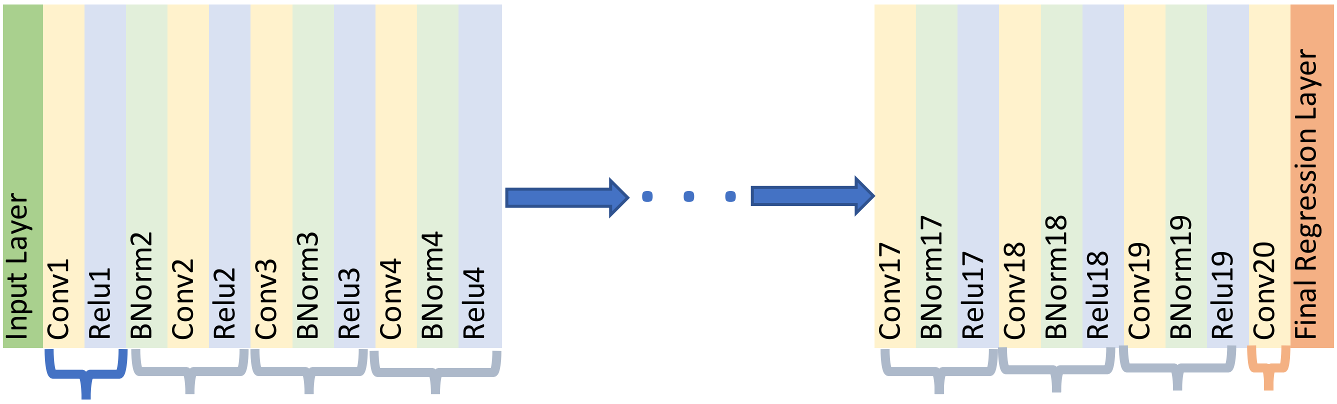


Figure 1. Applied DnCnn architecture.

$$x_{i,j}^{l} = \sum_{a}^{n}\sum_{b}^{n} w_{ab} y_{(i+a)(i+b)}^{l-1} \quad (1)$$

In the convolution layer, there is the activation phase after the convolution. Instead of activation functions such as sigmoid and tangent hyperbolic used in classical neural networks, the relu function in Eq. (2) is used in DnCNN. This non-linear function ensures that negative values in the image are eliminated.

$$y = \max(0, x) \quad (2)$$

In the last step in the convolution layer, the pooling process is performed. In this process, the low-dimensional images obtained after removing the maximum, minimum, sum or features on the local image matrix are transferred to the classification layer. The error value calculated at the output is used to update the convolution filter coefficients and the weights of the layers of the fully connected structure. This approach is typical feature of backpropagation networks. Hyperparameters of CNN are not learned directly, but define their properties. Selection of parameter is the most critical factor determining the performance of the method.

Table 1. DnCNN design parameters.

Network design feature	Value
Network depth	20
Convolution filter size	3x3x64
Stride	[1 1]
Padding	[1 1 1 1]
Error	Mean square error

Krizhevsky et. al. and his associates revealed the importance of convolution layers in design and the performance of architecture on big data [23]. For these reasons, it is observed that the correct determination of the design parameters is the most important criterion affecting the result.

2.2.2 Wavelet Denoising

The purpose of noise removal is to make the components that form the basis of the image much more distinguishable from the parts that do not belong to the image. In this way, the most important features of the image are preserved and the noise, which is not the main component of the image, is removed [24]. Since wavelet transform is a method that performs by separating the image into components, it provides success in removing many noises. The noise removal operation with wavelet transform consists of 3 main steps, namely separation into components, thresholding and inverse transform. Firstly, the wavelet and decomposition level are selected. The wavelet transform is applied to the signal. And wavelet coefficients are obtained. The details and approximations of the signal are obtained from these wavelet coefficients.

In the second step, thresholding is selected for each decomposition level and soft thresholding is applied to the detail coefficients. Finally, the inverse wavelet transform is obtained by using the approximation coefficients of the signal at the last decomposition level and the thresholder detail coefficients from 1 to the last level[25].

2.2.3 Bilateral Filtering

Bilateral filtering is used Gaussian kernels for image filtering. Bilateral filter is a kind of anti-aliasing filter that protects the edges and reduces noise as a result of its non-linear application for images. The intensity of each pixel in the image is based on varying the neighboring pixel values by calculating the average intensity values. The intensity of each modified pixel here is not just dependent on the Euclidean distance between pixels. At the same time, it also changes with different features such as depth distance and color density in the image. Thus, it is ensured that the significant points in the image are preserved [26]. The bilateral filter creates an intensity value combination that takes into account both geometric proximity and visual similarity, while favoring near pixels away. Geometric proximity refers to spatial similarity, while visual similarity refers to spectral similarity. Therefore, a bilateral filter can be defined as a combination of two Gaussian filters, spatial and spectral.

$$Y_x = \frac{1}{w_p}\sum_{x_i \in \Omega} Y(x_i) f_r(\|Y(x_i) - Y(x)\|) g_s(\|x_i - x\|) \tag{4}$$

Y_x: Output image
x: Input image
Ω: Window centered on the pixel to which the filter will be applied $x_i \in \Omega$:
f_r: Function used to smooth out the differences between pixels
g_s: Spatial function used to smooth out the differences between coordinates

2.2.3 Types of Noises

One of the most well-known noise models is Gaussian noise. this type of noise is sampling of the gauss distribution and therefore proceeds additively. To summarize, each pixel value in the noisy image in Gauss noise consists of the sum of the actual pixel value and the noise value generated as a random Gaussian distribution [27] (Eq. (3)).

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} * e^{(x-\mu)^2}/2\sigma^2 \tag{3}$$

σ: mean
μ : standard deviation

Impulse response, which is widely used in image and signal processing, models this type of noise. For this reason, it is used in the literature as impulse noise or salt&pepper noise. It is also called instantaneous noise, random noise or independent noise. Salt and pepper noise causes the image to deteriorate by changing the pixel values in an image to 0 or 255 at the minimum and maximum gray level. In salt and pepper noise, the value of 255 means salt noise and the value 0 means pepper noise[28]. This type of noise is observed as black and white dots on the image. For this reason, it appears as sharp and sudden changes on the image. Dust particles or overheated faulty components can cause this type of noise.

Poisson or shot photon noise is the noise that can occur when the number of photons detected by the sensor is not enough. This noise mathematically has a root mean square value proportional to the square root density of the image. Therefore, different pixels are affected by their individual noise values. It creates non-homogeneous decay in signals at different rates. Best results are obtained by using methods such as non-local averaging filter, biliteral filter, block-matching and 3D filtering (BM3D) algorithms [29] and wavelet applications to remove Poisson noise.

It is a type of noise that is more common in medical images. This noise is modeled by multiplying pixel values with random values.

$$P = I + n * I \tag{5}$$

N: speckle noise distribution image
I: input image
n: uniform noise image with mean and variance

In the case of ultrasound images, speckle noise arises when a sound wave arbitrarily hits small particles or wavelength that interferes with a scale equivalent to sound. Speckle noise is a random type of noise. Many different methods are used to fix it.

3 Results & Discussion

All images used in this study are images of pediatric patients. The most common difficulties faced by pedodontists are the movement of pediatric patients during the panoramic x-ray and the inability to control their breath during the extraction. For this reason, it causes several problems especially noise in the images. Two sample are shown in Fig. 1 and 2.

In this study, Gaussian, salt&pepper, speckle and poisson noises are frequently used in the literature. Noisy images are shown in Fig. 2.

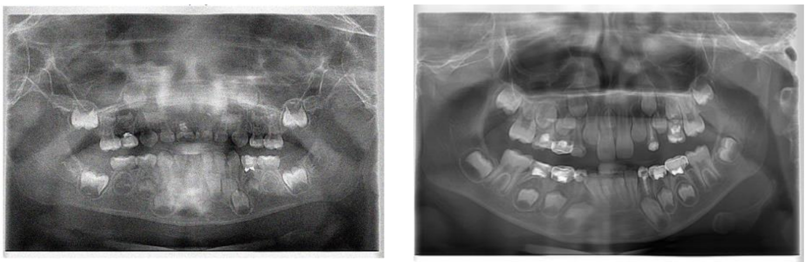


Figure 1. Sample 1 & 2 original images.

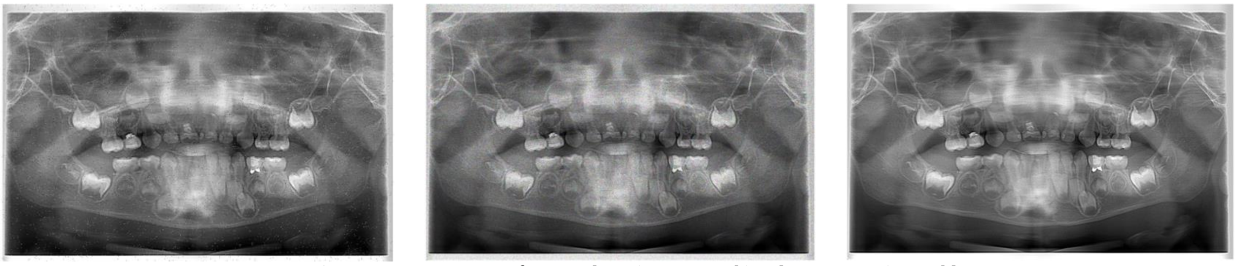


Figure 2. Noisy images for sample 1 a)Gaussian, b) Salt&Pepper, c) Speckle.

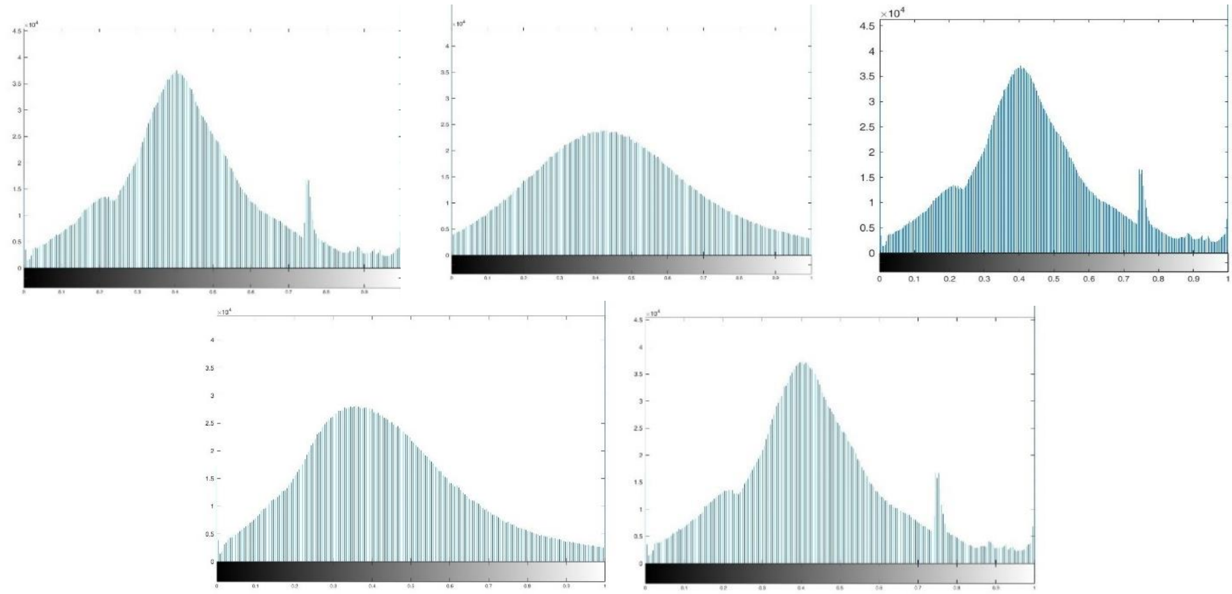


Figure 3. Original and different noisy images histograms for sample a) Original image b) Gaussian noisy image c) Salt&pepper noisy image d) Speckle noisy image e) Poisson.

Histograms are graphs that show the values of pixels containing images. The image histogram shows how many pixels are detected by detecting pixels at each point of the image. In this way, various information about the image is extracted from the histogram. Adding noise causes changes in the histograms of the images. Because the pixel values corresponding to the mathematical functions that make up the noise affect the distribution. The effects of different noise types on the histogram are shown in Fig. 3.

DnCNN, biliteral filtering and wavelet filtering were used to remove the noise from noisy image. The results obtained after applying all methods were compared by calculating peak signal to noise ratio (PSNR) and structural similarity index (SSIM) values.

PSNR and SSIM, which are the performance criteria commonly used in noise removal applications in the literature, were used to compare the results obtained from the methods used in this study. Firstly, we briefly explain these approaches [30]–[35]

The PSNR scale calculates the ratio of the peak signal to the power of noise between two images. The peak signal represents the actual value, and the noise represents the error. The higher the PSNR, the better the quality of the image. PSNR is expressed as shown in equation (4). In this equation, the max value represents the maximum peak signal value in the original image and the MSE scale value[30].

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n=1}|f(m,n) - f_n(m,n)| \quad (6)$$

$$PSNR = 20\log_{10}\left(\frac{max}{\sqrt{MSE}}\right) \quad (7)$$

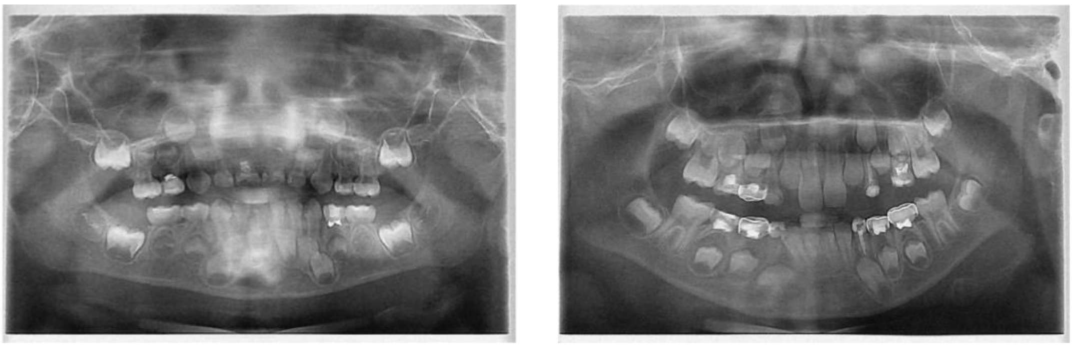
SSIM scale measures differences between original and reference images. The difference of PSNR is that it is based on visible structures. This scale can be computed via different image windows[30].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (8)$$

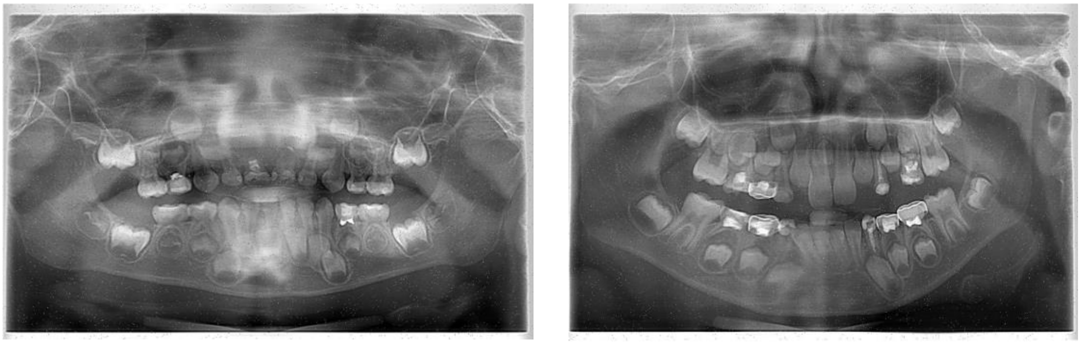
x, y: windows
σ: covariance
σ^2: variance
c_1, c_2: constants

SSIM scale should be (-1,1) range. If the SSIM value goes to 1, image quality increases. The SSIM scale measures the perceptual difference between the original image and the reference image. Unlike PSNR, it relies on visible structures in the image. This scale is calculated in various windows of the image

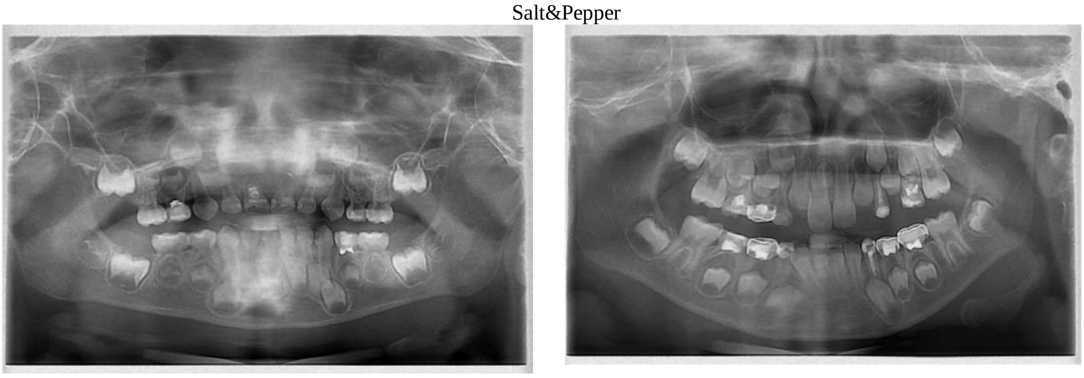
Performance evaluations of the results obtained from all methods used were made by comparing PSNR and SSIM values. Tables 2 shows the averages PSNR and SSIM values of denoised images of 30 test images with four different noise types and three different methods.



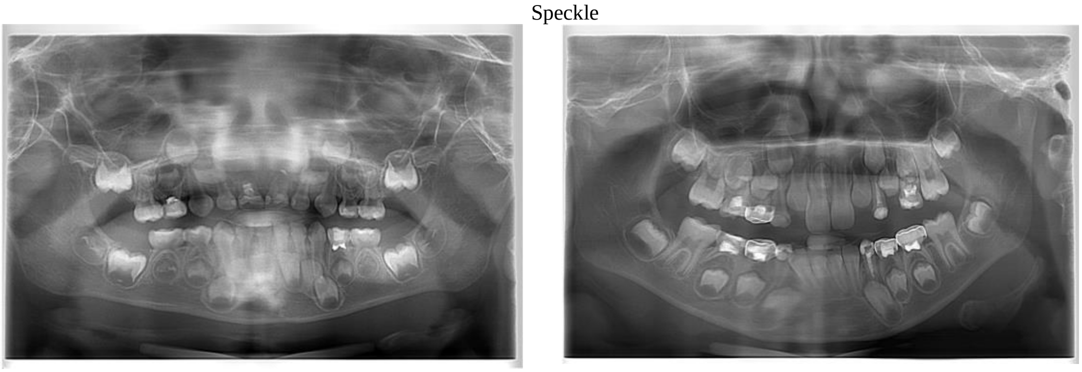
Gaussian



Salt&Pepper



Speckle



Poisson

Figure 3. DCNN sample 1&2 result images for different noise.

The average of the values obtained after applying to 30 images was calculated. These samples used for evaluation not training process. These values are shown in Table 2.

When the values obtained because of the analyzes are examined, it is seen that the noise removal performance of the DCNN method for all noise types used within the scope of the study surpasses other methods. Biliteral and wavelet-based methods, on the other hand, seem to lag in general, although they are more successful in eliminating Poisson noise in other noise types.

Table 2. Performance comparison PSNR&SSIM values for different noise.

	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
	Gauss		Salt&Pepper		Speckle		Poisson	
DCNN	**30.1000**	**0.7349**	**26.9511**	**0.7331**	**30.1628**	**0.7740**	**47.4974**	**0.9907**
Wavelet	29.5358	0.7240	25.3221	0.6856	26.7186	0.5554	39.6794	0.9361
Biliteral	23.6552	0.3309	26.1371	0.7075	25.6357	0.4502	38.0243	0.9100

4 Conclusion

Deep learning-based image enhancement methods significantly reduce image noise. It has been observed that its performance is more prominent than traditional noise removal methods. It is thought that performance improvement can be achieved by trying different neural networks or newly created hybrid models in future studies. In addition to the existing processes, the performance of the method proposed in this study can be increased with different pre-processing methods.

In denoising, the absence of residual images after denoising and preserving the image's qualities such as smooth features and edges are important issues. Since traditional methods usually focus on a single noise type or one or several features in noise removal, the desired performances cannot be fully captured in the resulting images. This situation has been partially avoided in noise removal studies using deep learning. It has been observed that more successful results are obtained by using networks with a deeper architecture during noise removal.

It should not be overlooked that as the depth of the network increases, more memory resources are consumed, excessive learning and lost slope problems occur.

Deep learning methods try to obtain the original image by making statistical calculations in order to minimize the loss values thanks to feedback networks. Finding a good loss function that fits well with the human visual system is an important research topic, as loss functions greatly influence the behavior of noise removal networks.

In future studies, hybrid models should be developed, not limited to a single deep learning architecture. The deep learning architectures to be developed should be examined according to their performance values at various noise levels, considering the proposed methods, the quality of the dataset, the training period and the proximity to the original image. Before deep learning methods are trained, performance evaluation can be made by developing different preprocessing processes.

Declaration

Ethics committee approval is not required.

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