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ORIGINAL RESEARCH ARTICLE

Impact of Selective median filter on dental caries classification system using deep learning models

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ABSTRACT

Accurate classification of dental caries is crucial for effective oral healthcare. Filters help to increase exposure of the picture taken for the investigation without degrading image quality. Selective median filter is the chosen preprocessing technique that helps to reduce the noise present in the captured image. Dental caries classification system is a model used to detect the presence of cavity in the given input image. Dental caries classification system is evolved with the use of conventional techniques to artificial neural network. Deep learning models are the artificial neural network models that can able to learn the features from the raw images available in the dataset. If this raw image has noise, then it severely affects the accuracy of the deep learning models. In this paper, impact of the preprocessing technique on the classification accuracy is analyzed. Initially, raw images are taken for training on deep learning models without applying any preprocessing technique. This study investigates the impact of Selective median filtering on a dental caries classification system using deep learning models. The motivation behind this research is to enhance the accuracy and reliability of dental caries diagnosis by reducing noise, removing artifacts, and preserving important details in dental radiographs. Experimental results demonstrate that the implementation of Selective median filtering significantly improves the performance of the deep learning model. The hybrid neural network (HNN) classifier achieves an accuracy of 96.15% with Selective median filtering, outperforming the accuracy of 85.07% without preprocessing. The study highlights the theoretical contribution of Selective median filtering in enhancing dental caries classification systems and emphasizes the practical implications for dental clinics, offering improved diagnostic capabilities and better patient outcomes.

Keywords: dental caries classification system; preprocessing; Selective median filter; deep learning models; accuracy; performance

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1. Introduction

Radiology is the medical imaging technology which is used in diagnosis and sometimes in the treatment of diseases. X-rays are waves that have a comparatively high frequency in the electromagnetic spectrum. They are transmitted or absorbed by different parts of body in different amounts. X-ray images make diverse shades of black and white. Generally, bone appears in white, soft tissue appears in gray and air shows black. Digital images are obtained using one of two methods in digital radiography by having the X-ray that pass to the patient body and fall openly on to the devices which change X-rays to light by digitizing X-ray films Samei[1]. Dental diseases are avoidable diseases. Identification of cavity infection or dental diseases is necessary for avoiding several oral disorders. X-rays images are generally used in medical diagnostics. X-ray technology is nowadays used for identifying different stages of cavities. This rising technology, in combination with dental care, provides a cost-effective treatment to better prevent tooth loss and decay. Dental X-ray gives pictures of teeth, bones, and other adjacent areas. X-ray pictures can show cavities, unnoticed dental structures, and other damages to teeth that cannot be identifying during a visual assessment[2]. Dental X-rays are taken when you need them depending on your age, risk and cryptogram of disease.

Smoothing is necessary for noise reduction and blurring of fragments of the wrong contour and to increase the overall visual superiority of the corrupted image. Spatial or frequency domain systems can be used for cleaning an image and improvement to its properties. In the Fourier domain, the frequency domain uses filtering. On the other hand, space domain techniques normally use non-linear or linear spatial operations. Many effective methods are seen in the spatial domain. Averaging over a predefined neighborhood is the simplest smoothing technique. This significantly reduces noise, while also blurring the edges of the object[3,4].

Image enhancement techniques are of two types: 1) spatial domain manner; 2) frequency domain manner Spatial Domain Technique: mean filter is the simplest amount of smoothing algorithms. Mean filtering is a modest, sensitive and easy method used to smooth medical images, which reduces the difference in intensity between one and the other pixels[5]. It is commonly used in MRI images to reduce noise. Medium filtering is intended to substitute each pixel in an image with its neighbors' average value, with itself. It reduces the pixel values that do not show their background. Frequency Domain Technique: it depends on the orthogonal transformation of the image rather than the image itself[6]. The frequency domain techniques relate to the frequency content processing of the image. Orthogonal transformation of the image consists of two components. The frequency content of the image consists of magnitude. The phase is used for restoration of the image back to the spatial domain[7].

There are several types of oral diseases such as cavities, plaque, caries etc. generally all these diseases diagnose by oral expert or dentist by examine the patient or by taking dental X-ray images. Digital radiography is a boon in the health care sector. It helps diagnosis of the human body[8]. Medical imaging systems are seen in many application areas but still there is room for the further improvements. Medical images may be corrupted by various types of noise signals; which degrade their quality hence it is essential to reduce the effect of noises. Filters are used for this purpose. Filtration may suppress important features which may cause any false interpretation done by the radiologists[9]. Deep learning models are used to detect the caries[10]. Rahimi et al. demonstrated the impact of preprocessing techniques on word embedding quality[11]. Xiao et al. demonstrated the impacts of data preprocessing and selection on energy consumption prediction model of HVAC systems based on deep learning[12].

Motivation behind studying the impact of Selective median filtering on dental caries classification systems arises from the necessity to enhance the accuracy and reliability of dental caries diagnosis. By reducing noise, removing artifacts, and preserving important details, Selective median filtering holds the potential to improve the quality of dental radiographs and optimize the performance of caries classification algorithms.

Section 2 discusses the basic concepts such as noise in digital images, image de-noising algorithms. The Selective median filter is discussed in the third section. The next section describes the hybrid neural network classification algorithm, which is a mix of stacked sparse auto encoder and Logistic regression classifier. The section 4 contains results and explanation of the classification method, which is analyzed for various preprocessing procedures. Following that, the conclusion is presented.

2. Basic concepts

2.1. Noise in digital images

Noise in an image may be either additive or multiplicative. Both additive and multiplicative operations are done at the pixel level. Noise introduced in images is of two types[13]. However, image may also be corrupted by sparse noise, shot noise etc. Sparse noise does not affect all the pixels of an image but affects few of them and this effect is severe. Salt & pepper noise comes into this category[14]. Shot noise, also known as quantum noise or Poisson noise, is a type of statistical noise that arises from the discrete nature of photons or particles in a signal.

2.1.1. Gaussian noise

It is the example of additive noise. It is also called as white noise due to its even distribution over the signal. If this noise is introduced in any image then the noisy image contains noisy pixels[15]. Each noisy pixel is the sum of actual pixel value and the randomly distributed Gaussian noise values. The probability distribution function (PDF) of Gaussian noise is given by:

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(g-m)^2}{2\sigma^2}} \tag{1}$$

Equation (1) is identified as the Gaussian filter probability density function, where g identified as the grey scale level and σ identified as the standard deviation of the noise, and m identified as the average function[16].

2.1.2. Salt & pepper noise

It is an example of impulsive noise which has only two possible values a and b. It appears in the form of white and black dots in the image with the appearance of Salt and pepper. If an image has pixels in which each pixel is represented by eight bit of noise, its value is 0 and Salt noise is 255. It comes under the category of sparse noise as it does not to have any effect on all the pixels of any image but affects only few pixels randomly. It can cause malfunctions of pixel elements in the camera sensors or defective memory positions due to errors in the digitization procedure[17].

2.1.3. Speckle noise

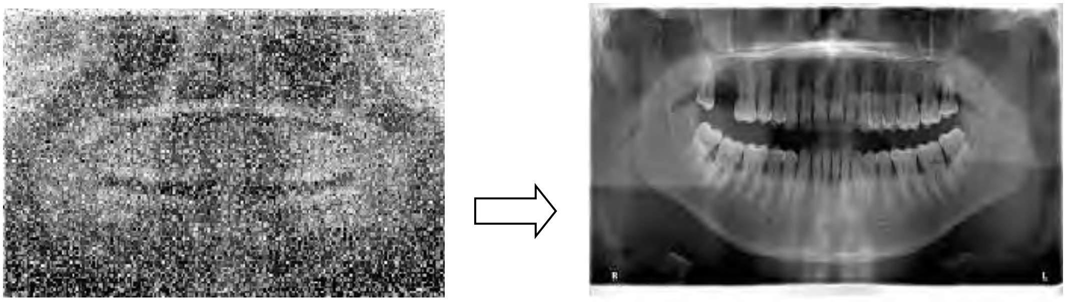
It comes under the category of multiplicative noise. Any image introduced multiplied by the true pixel value of the noise free image. It occurs in coherent imaging schemes, e.g., laser, acoustics and Synthetic Aperture Radar (SAR) images etc. Random inference among the coherent returns is the source of Speckle noise[18]. The PDF of Speckle noise is given by:

$$f(g) = \frac{g^{a-1}}{\gamma(a) * \theta^a} e^{\frac{-g}{\theta}} \tag{2}$$

In Equation (2) where, g represents the intensity of the Speckle noise and a is the shape parameter, θ is the greyscale level of an image and $\gamma(a)$ is the gamma function.

2.2. Image de-noising

This is a pre-processing task in image processing. Suppression of noise signals and preservation of the useful information of the images such as edges, fine structures, texture details etc. are the main goals of image de-noising[19]. Many methods have been implemented for image de-noising but no method provides the satisfactory results for different types of noise problems. Hence, a framework has been developed which not only removes different noise signals but also preserves the image information. **Figure 1** shows that the noisy to de-noised dental image[20].



(a) Noisy image **(b)** De-noised image

Figure 1. Conversion of noisy to de-noised dental X-ray image.

In image de-noising field, there are several filters are used in pervious medical image de noising applications. However, some of the filters can eliminate only the noise and enhance the medical image in quality manner. So here some filter features and de noising manner of few filters are discussed.

2.2.1. Median filter

This is the most common filter used for removal of Salt & pepper noise. In this filter square window of size $(2x + 1) \times (2x + 1)$, where x represents the radius of the window is used. For example, when $x = 1$, the window size will be 3×3. In this filter the smallest window size is 3×3. Other popular sizes are 5×5, 7×7, 9×9, etc. In this filtration technique; the central pixel is swapped by the value which is the median of the neighbor pixels within the window[21].

It reduces impulse noise but cannot remove Gaussian noise. Performance of this filter can be improved by increasing the window size, i.e., larger the window size; better the noise suppression. However, large window size increases the relocation on the edges of the image. It provides better results than the averaging (mean) filter in which the central pixel is swapped by average values of neighbor pixel values within the window. **Figure 2** illustrates that the Median filter matrix concept.

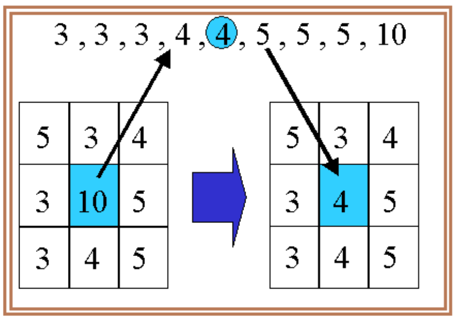


Figure 2. Median filter matrix.

2.2.2. Average filter

The powerful linear filter is the Average filter. This filter is the simplest and the easiest way to smooth images, minimizing of the intensity variation of the next pixels. It is used frequently to reduce noise in pictures. The processing element value in a pixel matrix is substituted by the filtering concept with the average value of its neighbors. It repeatedly deletes those pixel values that do not represent environment. The Average filter corresponds somewhat to the convolution filter. The kernel also represents the shape and dimensions of the surrounding area to be sampled during calculation by the average. In practice 3×3 square kernel is common. However, when the high smoothing requirement occurs, bigger kernels such as 5×5, 7×7 can be used. Average Filter reads the input picture and sets the output picture header information[22].

2.2.3. Wiener filter

The fundamental concept behind the Wiener filter involves designing a frequency-domain filter that can be applied to the degraded image. This filter aims to reduce noise while preserving important image features. The Wiener filter takes into account the statistical properties of both the degraded image and the noise[23]. The Wiener filter comes from a different perspective. By applying the Wiener filter, noise components are attenuated based on their frequencies, while important image features are preserved. The Wiener filter seeks to strike a balance between noise reduction and image fidelity. The formula for the Wiener filter in image processing is

$$G(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + K(u,v)} \tag{3}$$

where $H^*(u, v)$ is the Fourier transform of complex conjugate of the degraded function, $K(u, v)$ is the reciprocal of the SNR and $H(u, v)$ is the degraded function.

3. Experimental methods

3.1. Selective median filter

In this module, the different filters to eliminate the noise in Dental X-ray images have been proposed. These involve the analysis of filter efficiency by taking three different noises namely Salt and pepper, Gaussian and Speckle noise. The noise reduction filtering such as Average filters, Median filter, and Wiener filter are used. By this different filtering method, images with these three noises are given to for analysis of the de-noising efficiency. Input images are added with noise. Noise added images are de-noised with the help of different filtering techniques. Performances of the various filters are analyzed by comparing the mean square error value. From the comparison Selective median filter is designed which reduces the above three different noises effectively.

Here, the Selective median filter acts as a Median filter for the pixel value 0 and 255. For other pixel values it acts as Wiener filter[24]. Application of the three filters helps obtaining different parametric value for calculation and analysis of the filter efficiency and determines which is better for particular noise condition in dental X-ray imaging field. **Figure 3** mentioned that the flow of proposed filtering technique. Efficiency of the proposed method can be calculated in terms of parameters such as MSE, which are clearly explained and evaluated as following section.

3.1.1. Mean square error

The difference between two images is taken using the pixel by pixel value for calculation of MSE. Then it is squared and finally average is taken. MSE between both is zero when both the input images are found to the same in all aspects. Let images I1(i, j) and I2(i, j) are two different gray scale images with size $M \times N$ then MSE between both the images is given as:

$$MSE = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [I_1(i,j) - I_2(i,j)]^2 \tag{4}$$

Equation (4) shows decrease in MSE decreases with increase in peak signal-to-noise ratio (PSNR) values. Higher PSNR value between de-noised and test image indicated the superior performance of any technique. The main goal of any de-noising method is to achieve higher PSNR values. However, higher PSNR value does not imply that visual quality of de-noised image is good. Hence, other parameters were also required which may indicate qualitative analysis of the proposed method. Structural Similarity Index (SSIM) is one of the parameters used for qualitative analysis which is to be calculated between test images and de-noised images.

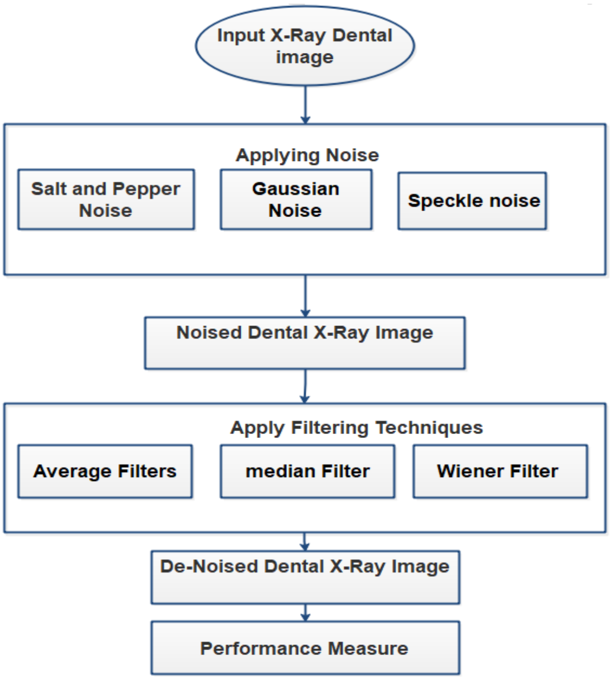


Figure 3. Steps in preprocessing.

3.2. Hybrid neural network for dental caries classification

The new technique for the detection of caries is dependent on its form and therefore accurately classifying the caries affected layer is recommended in this section. HNN is the mixture of Artificial Neural Network (ANN) and Deep Neural network (DNN). The DNN uses the stacked sparse auto-encoder for achievement of image classification. Authentic information can then be obtained by supervised fine tuning and unattended pre-training from the data. On the other hand, ANN relies on the logistic regression for the classification of the denture affected sheet. **Figure 4** signify the dental caries architecture design. The input dental images are given to the hybrid neural network model, here the researcher has two different classifiers namely sparse auto encoder and Logistic regression classifier model, and these classifiers classify the teeth in layer wise order and provide the performance results[25].

The method generates an efficient output against the supplied input image and categorizes the decay level precisely. The ground-breaking technology for hybrid neural networks provides good results in accuracy and processing time.

The hybrid neural network consists of two models namely Stacked Sparse Auto-Encoder and Logistic regression classifier, which are described in following section.

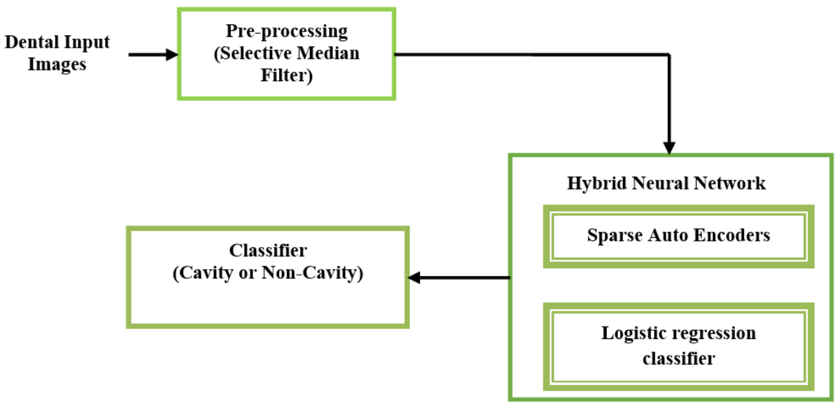


Figure 4. Block diagram of dental caries classification system.

3.2.1. Stacked sparse auto-encoder

The stacked sparse encoder is a symmetrical neural network that has unregulated data set functionality. In this research work, DNN uses SSAE (sparse auto-encoder stacked) which is trained to extract hidden features in an uncontrolled fashion. The cavity in dental images was detected and encoded into sparse maps which encoded both the appearance and the cavity position. The stacked sparse auto encoder was used for the identification of the cavity and it learnt the features in a single network. In the first stage of SSAE, background and cavity regions were trained in patch. The threshold technique was initially used for identification of the cavity regions. The other areas are taken as the background. The cavity and background regions in cross-section sparse are multiplied. No universal activation of neurons is performed in this layer. Primary regions are allowed, background regions are not enabled. This technique helps the background to be emphasized. 6 convolution and 2 pooling layers were used in the initial stages of the neural network[25]. In the final stage the map consisted of two functional maps, the first of which was the detection map and the second of the background map. The original map and the background map were combined and have been shown as a reconstructed image. The image was reconstructed by summarizing the front and background images.

3.2.2. Logistic regression classifier

Regression logistics is a predictive analysis that describes the relationship between dependent and independent variables. A single variable exists as also one or more variables exist. The Logistic regression classifier helps identification of the affected dental cavities. The adaptive coefficient comprises the key characteristics, and hence can help improvement of the accuracy of the classifier. The logistic regression classification is used to change the unregulated result achieved through the stacked sparse car encoder. **Figure 5** shows the Logistic regression classifier with this binary and multi class classification method.

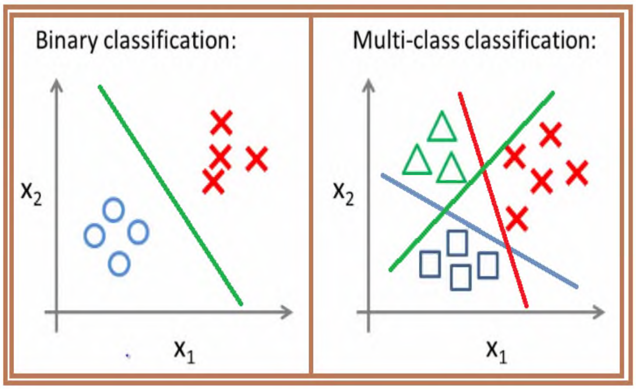


Figure 5. Logistic regression classifier model.

The suggested model looks to examine how preprocessing affects deep learning models. The preprocessing method utilized is the Selective median filter, and the deep learning models chosen are hybrid neural networks. In the respective processing, both strategies outperform other conventional procedures. The analysis's goal is to determine the hybrid neural network's accuracy by feeding it raw data. Here, raw data refers the image in the database before applying the preprocessing operation. In the second stage of analysis, preprocessed image is given to the hybrid neural network. Accuracy is figured out. The HNN's accuracy with both preprocessed and raw pictures is compared.

4. Results and discussion

MATLAB environment is used in the implementation of this method. Various dental X-ray images have been used. Three noises have been synthesized for creation of bright dental X-ray inputs. Compared to the basic Median, Average and Wiener filter, Selective median filter is better. Dental images are given as the system input image. Input images are added with the Salt and pepper noise, Gaussian noise and Speckle noise at various proportion from 10% to 60%. Mean square error (MSE) is computed before applying the filter. After that MSE value is computed for the noised images and de-noised images with Average filter, Median filter, Wiener filter and the Selective median filter. **Table 1** shows the MSE parametric values obtained from Salt & pepper noise using the three different filtration techniques. **Figure 6** is the graphical presentation of table parametric values. Noise values in *x* axis at 10% to 60% and *y* axis of MSE are taken into account. The graph shows that the MSE value of Salt and pepper noise in different filter.

Table 2 shows the MSE parametric values obtained from Gaussian noise using the three different filtration techniques. **Figure 7** is the graphical presentation of table parametric values of different filtering methods under Gaussian noise condition. *X* axis denotes noise density at 10% to 60% and *y* axis refers to MSE values. The graph shows the MSE value for different filters. The conclusion is that the Wiener filter reduces Gaussian noise efficiently.

Table 1. MSE values of filters on images with Salt & pepper noise.

	MSE value				
Noise density	**Before filtering**	**Average filter**	**Median filter**	**Wiener filter**	**Selective median filter**
10%	0.0029	0.000801	0.0000234	0.0015	0.0000214
20%	0.0056	0.0012	0.000024	0.0023	0.0000226
30%	0.0082	0.0015	0.0000554	0.0027	0.0000521
40%	0.0116	0.0018	0.0000602	0.0032	0.0000593
50%	0.0142	0.0022	0.0000621	0.0036	0.0000618
60%	0.017	0.0025	0.0000789	0.0038	0.0000778

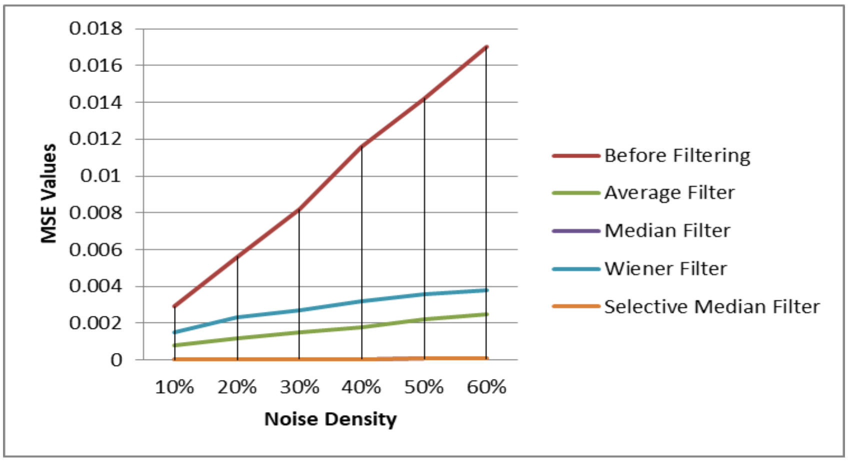


Figure 6. Comparison of MSE values of filters on images with Salt & pepper noise.

Table 2. MSE values of filters on images with Gaussian noise.

	MSE value				
Noise density	**Before filtering**	**Average filter**	**Median filter**	**Wiener filter**	**Selective median filter**
10%	0.0097	0.0016	0.0017	0.0006	0.00043
20%	0.0191	0.0027	0.0034	0.0015	0.0012
30%	0.0277	0.0037	0.0052	0.0021	0.0017
40%	0.0358	0.0048	0.0068	0.0029	0.0024
50%	0.0434	0.0057	0.0084	0.0035	0.0028
60%	0.0505	0.0065	0.0101	0.0042	0.0037

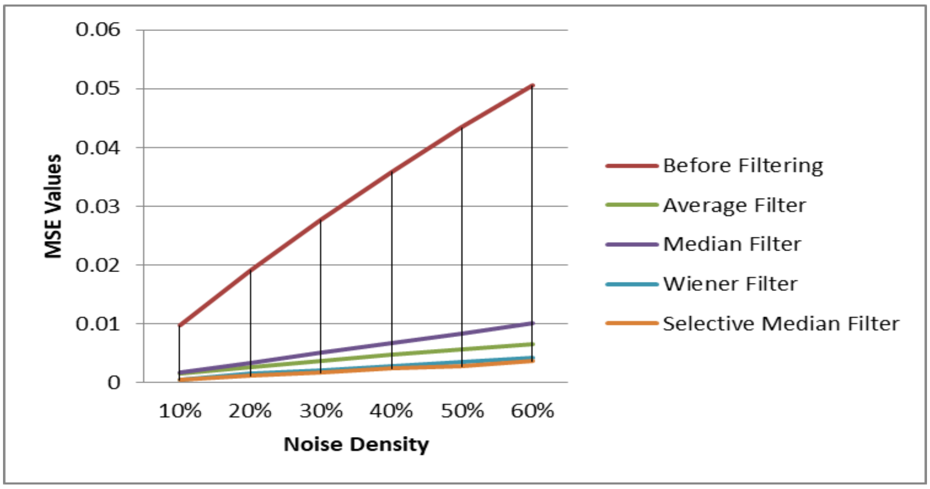


Figure 7. Comparison of MSE values of filters on images with Gaussian noise.

MSE values are obtained for the filters discussed earlier at different noise density on the Speckle noise added image. **Table 3** shows the filter obtained different parametric values under the noise of Speckle condition. **Figure 8** is a graphical representation parametric values, as the same as in the table. The graph shows MSE value is low for Wiener filter.

Table 3. MSE values of filters on images with Speckle noise.

MSE value					
Noise density	**Before filtering**	**Median filter**	**Average filter**	**Wiener filter**	**Selective median filter**
10%	0.0024	0.000687	0.0008	0.000233	0.00016
20%	0.0047	0.0014	0.0011	0.00051	0.0004
30%	0.0071	0.002	0.0014	0.000855	0.00071
40%	0.0094	0.0027	0.0017	0.0012	0.00091
50%	0.0117	0.0034	0.002	0.0016	0.00115
60%	0.014	0.004	0.0023	0.0019	0.00157

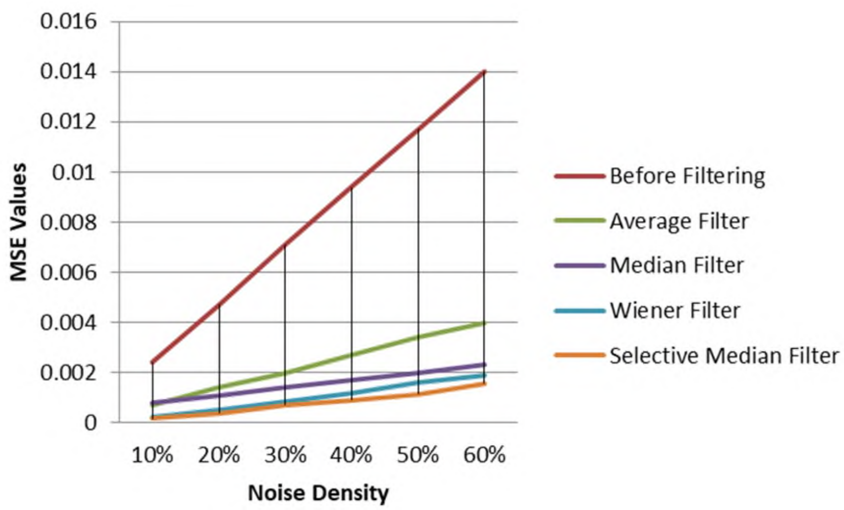


Figure 8. Comparison of MSE values of filters on images with Speckle noise.

This comparison analysis helps the conclusion of Wiener filter is efficient for reduction of the Speckle noise. In above analysis, we study the effect of three noises on dental images and the effect of three filters on this noise added images. This analysis helped to design Selective median filter which is also called as adaptive Median filter. Since it is a variant of Median filter. MSE values are determined for the conventional and proposed Selective median filter. Graph shows that Selective median filter outperforms the conventional filters.

Designed pre-processing techniques have the impact on the classification model used in the following chapters. Selective median filter is applied on the images of the Dataset. The database has been obtained from the website (http://www-o.ntost.edu.tin/~cweiwang/ ISBI2015/). 80 pictures were given to the dataset. The training data set included 40 pictures and the evaluation dataset contains 40 pictures. There were six or more teeth in each photo. Each teeth image was separated into 6 teeth images for simplification of this process. 480 dental images are available in the final data sets. 300 images are taken for training process and 180 for testing process. Around 173 images are correctly identified and detected with accurate results in sheet. The complete creation of essential medical data is performed in the MATLAB environment. **Table 4** represents the accuracy value of different filtering techniques.

Table 4. Classification accuracy of filters.

Filtering techniques	Classification accuracy
Without noise removal	85.07%
With Selective median filter	96.15%
With Median filter	93.67%
With Wiener filter	92.43%
With Average filter	87.08%

The accuracy value of the HNN is shown in **Figure 9** both with and without the use of a noise-removal approach. The accuracy of the HNN classifier without the noise removal method is 85.07%, which is lower than the accuracy value of the HNN when preprocessed images are employed. Selective median filtering of images yields an accuracy value of 96.15%. HNN with a Selective median filter performs better than the other traditional methods. According to this analysis, preprocessing significantly improves the deep learning model's accuracy.

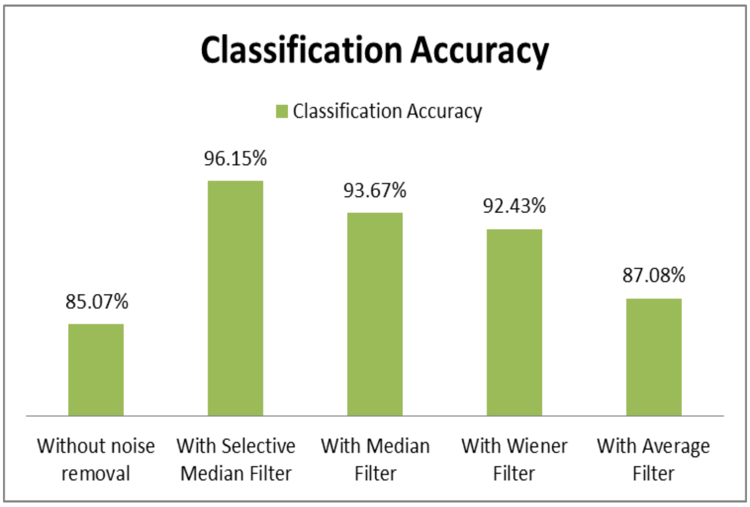


Figure 9. Accuracy of HNN classifier.

Table 5 compares the accuracy, recall, and F1 Score values of different filters. When compared to other filtering strategies, the hybrid neural network that employs the Selective median filter as the preprocessing strategy performs well. The accuracy, recall, and F1 Score values for HNN classification for various preprocessing filters are shown in **Figure 10**. HNN without preprocessing yields an accuracy value of 85.07, a recall value of 85, and an F1 Score value of 85.03. It has the lowest value of the techniques. HNN, on the other hand, delivers the maximum accuracy value of 97.01, recall value of 95.79, and F1 Score value of 96.4 when using the Selective median filter as the preprocessing approach.

Table 5. Comparative analysis of precision, recall and F1 Score of HNN classification for various preprocessing filters.

Filtering techniques	Precision	Recall	F1 Score
Without noise removal	85.07	85	85.03
With Selective median filter	97.01	95.79	96.4
With Median filter	93.67	93.6	93.63
With Wiener filter	92.43	92.4	92.41
With Average filter	87.08	85.2	86.13

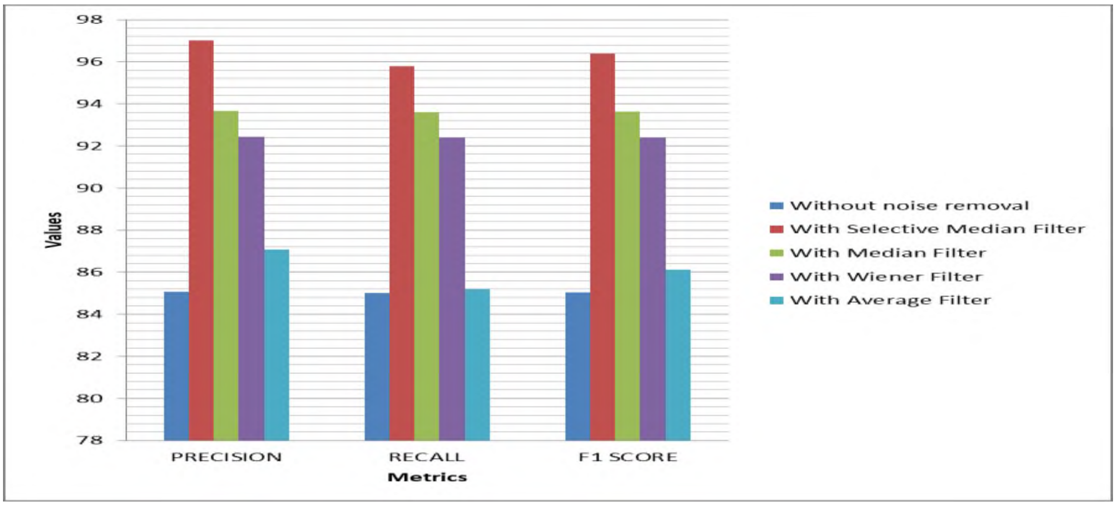


Figure 10. Precision, recall and F1 Score value for various preprocessing filters.

5. Conclusion

The paper aimed to assess the impact of Selective median filtering on a dental caries classification system utilizing deep learning models. The primary motivation behind this research was to enhance the accuracy and reliability of dental caries diagnosis by reducing image noise, eliminating artifacts, and preserving important details present in dental radiographs. The experimental results revealed a significant improvement in the performance of the deep learning model following the implementation of Selective median filtering. The accuracy of the hybrid neural network (HNN) classifier, when no noise removal method was employed, yielded an accuracy rate of 85.07%. In contrast, the utilization of preprocessed images through Selective median filtering yielded an accuracy value of 96.15%. These outcomes underscore the effectiveness of Selective median filtering in enhancing the accuracy of the dental caries classification system. Comparative analysis demonstrated that the HNN classifier employing the Selective median filter as a preprocessing technique outperformed alternative filtering strategies. The HNN classifier, combined with the Selective median filter, exhibited superior accuracy, recall, and F1 Score values. Specifically, an accuracy rate of 97.01%, a recall rate of 95.79%, and an F1 Score value of 96.4 were achieved. These findings reinforce the notion that Selective median filtering significantly enhances the classification accuracy and diagnostic capabilities of the dental caries classification system.

This study contributes to the existing body of knowledge by validating the theoretical proposition that Selective median filtering can effectively enhance dental caries classification systems utilizing deep learning models. It provides empirical evidence supporting the impact of this preprocessing technique on the performance of the HNN classifier. The study expands our understanding of image processing techniques in the context of dental imaging applications, thereby advancing theoretical knowledge in the field. The practical implications of this research are substantial for the dental profession and dental diagnostics. To increase the quality of dental radiographs, dental clinics and imaging centers can adopt Selective median filtering as a preprocessing step. By reducing noise, eliminating artifacts, and preserving critical details, Selective median filtering enhances the diagnostic capabilities of dental caries classification systems. This, in turn, enables more accurate and reliable identification of tooth decay, leading to improved treatment planning, timely intervention, and enhanced patient outcomes. This study provides empirical evidence of the theoretical proposition that Selective median filtering enhances dental caries classification systems utilizing deep learning models. The practical implications of this research are noteworthy, as the implementation of Selective median filtering has the potential to significantly improve the accuracy and reliability of dental caries diagnosis in real-world clinical settings.

Author contributions

Conceptualization, LML, TKR and AJS; methodology, LML; software, LML and AJS; validation, LML, TKR and AJS; formal analysis, LML; investigation, LML; resources, LML and TKR; data curation, LML and AJS; writing—original draft preparation, LML; writing—review and editing, LML, TKR and AJS; visualization, LML; supervision, TKR.

Conflict of interest

The authors declare no conflict of interest.

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