

# A Novel Method for Dental Radiographs Contrast Enhancement for Efficient Diagnosis of Dental Diseases

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**Abstract:** Contrast Enhancement for Low resolution image is an active area of research to attain an effective diagnosis results in the medical field through Digital Medical Images. To do this, a novel contrast enhancement method is proposed in this paper based on the spatial correlation characteristics of image pixels. Considering the spatial correlation as main factor, the proposed method focused to improve the contrast of center pixels based on its neighborhood pixels. Extensive simulations are conducted over the proposed method through several dental radiograph images and the obtained results are analyzed both qualitatively and quantitatively. The Quantitative analysis is done through a metric, called contrast root mean square deviation and the obtained values are compared with conventional contrast enhancement techniques, Histogram related methods and Contrast stretching methods.

**Keywords:** Dental Radiograph, Contrast Enhancement, Histogram, Correlation, CMRSD.

## I. INTRODUCTION

In recent years, there has been an increased effort in the development of an automatic computerized system for clinical research and applications in dentistry. Dental image analysis plays an important role in the treatment, clinical diagnosis and surgery of several dental related diseases. The dental radiograph images (DRI) can be used to discover concealed structures of dental images dental, benign masses or malignant cavities and bone losses. During the treatment or diagnosis processes such as diagnosis of caries, root canal operation, orthodontic patient's treatment planning, dental radiograph analysis is necessary. Basically the dental X-ray radiograph images are classified into 2 classes, i.e. the extra-oral ones and the intra-oral ones [1]. The intra-oral dental X-ray images includes the "bite wing X-ray images, occlusal X-ray images, and the periapical X-ray images". The "bite wing X-ray images" are used to represent the particulars about the lower and upper jaw in the mouth. The "occlusal X-ray images" are used to monitor the placement and development of the overall teeth arch in either lower or upper jaw. Further the "periapical X-ray images" are used to track the entire tooth. Instead, the extra-oral images helps in the finding of dental related problems in the skull and jaw, for example, the panoramic X-ray images and cephalometric projections.

Dental image diagnosis defines the elucidation of patient's dental, bony, and soft tissues arrangements and

also offer the entire images in the analysis of planning a treatment for orthodontic problems. But, in clinical assessment, tracking of anatomical (functional) structures of dental images is accomplished during the treatment preparation. This process consumes more and more time and also the process is subjective in nature. To overcome this problem, an automatic detection of dental landmarks like caries, occlusions, cavities and bone structures for diagnosis of orthodontic treatment is an optimal solution. But the detection of dental landmarks with high success rate and precision is a challenging issue. Several research contribution have been accomplished in this decade to build an automatic analytical system for dental image clinical purposes, like image segmentation [2, 3], anatomical landmark identification [4, 5], treatment and diagnosis [6, 7, 8].

In general an automatic image segmentation system accomplishes in two phases, preprocessing and detection. In the preprocessing phase, the input images are processed for feature level adjustments followed by features extraction. In the next phase, the extracted features are processed for detection through supervised learning techniques. Since the features of dental radiographs are more important, extraction of significant features is a challenging task and the proper features are only extracted when the input image quality is high and effective. Considering the quality of dental image as main objective, this paper proposed a new dental image contrast enhancement technique to make the dental image brighter such that the soft tissues and bones are more clearly visible. Further the proposed contrast enhancement technique also boosts the quality of low-contrast image to high contrast image. The simulations conducted over different low-contrast dental images shows the effectiveness of proposed mechanism.

Remaining paper is ordered as: section II discusses the particulars of literature survey. The details of proposed contrast enhancement method are described in section III. Experimental analysis details are enumerated and the conclusions are enumerated in section V.

## II. LITERATURE SURVEY

Since the intra-oral DRIs are low resolution (LR) images due to the low dose usage (LDU). The process of LDU is

Revised Manuscript Received on December 22, 2018.

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dependent on the health condition of patient [9, 10]. Hence the image enhancement techniques can be useful to the DRIs to increase the quality. Generally the image quality enhancement is accomplished through the manipulation of its contrast such that the tissues and bones in the dental image are clearly visible.

The most popular contrast enhancement (CE) techniques such as “Histogram Equalization (HE) [14], Adaptive Histogram Equalization (AHE) [15], and contrast limit adaptive histogram equalization (CLAHE) [16]” are being extensively used in the medical field to increase the contrast of LR images. HE results in the CE image with over brightness and also introduces noise and harshness in resultant image. Furthermore, the CLAHE tends to introduce some instantaneous changes at the borders of images through their grey pixel intensities. Since the architectures of DIRs are somewhat typical in nature, the quality improvement approach should be specific in nature. A study about the outcome of the novel HE on the quality of image in digital “periapical X-ray images” was carried out by M. Mehdizadeh and S.Dolatyar [11].

In [12], a new CE method is proposed to improve the quality in LDU X-ray images through wavelet features. By considering the corrections in the contrast, a new contrast enhancement is proposed in [13] through histogram registration (HR). This HR remodels the histograms of the 2 DRIs in such a manner that they are complemented with respect to their deviation in the contrast levels.

Further, in [17], a new method was proposed to increase the contrast of DRIs through a new method called “sharp contrast-limited adaptive histogram equalization (SCLAHE)”. Totally 10 intra-oral images periapical dental x-ray images are processed for evaluation. With an aim of improving the contrast of LR DRIs, [18] proposed a contrast stretching (CS) technique and also analyzed the evaluation of the variable CS technique. With an extension to the method developed in [17], an integrated method is proposed in [19] by combining three different CE techniques namely, “sharp adaptive histogram equalization (SAHE), sharp median adaptive histogram equalization (SMAHE) and SCLAHE”.

### III. PROPOSED METHOD

In this section, the complete details of proposed approach are outlined briefly. The proposed considers the spatial correlations between the GLs for contrast enhancement whereas the conventional approach didn't considered these spatial dependencies by which the GLs in the contrast enhanced image don't have any relationship with neighboring pixels which makes the entire process more complex and not clear. The complete details or proposed approach is outlined as follows;

For example, lets assumes an input image ‘*I*’ with height *H* and width *W* and having the gray-levels (GL) range of [*I<sub>d</sub>*, *I<sub>u</sub>*] and the enhanced image ‘*O*’ of range [*O<sub>d</sub>*, *O<sub>u</sub>*], having the visual perception quality better than the input image ‘*I*’. Mathematically these input and output images are represented as,

$$\begin{aligned} I &= \{I(m, n) | 0 \leq m \leq M - 1, 0 \leq n \leq N - 1\} \\ O &= \{O(m, n) | 0 \leq m \leq M - 1, 0 \leq n \leq N - 1\} \end{aligned} \quad (1)$$

Here the range of input and output images such as  $I(m, n) \in [I_d, I_u]$  and  $O(m, n) \in [O_d, O_u]$  varies from 0 to

255 for an 8-bit image. This range is ideal, i.e., 0-255 only if the enhancement process utilizes the entire dynamic gray-level range. In such case, the lower limit  $O_d = 0$  and the upper limit  $O_u = 255$ .

#### A. Spatial Entropy based Contrast Enhancement (SECE) [20]

Let the input image *I* has *K* discrete gray levels and the obtained gray levels after sorting them is  $\{I_1, I_2, \dots, I_K\}$ . Initially, the *I*s decomposed into various grids, distributed spatially. The 2D spatial histogram (SH) of a gray-level *I<sub>k</sub>* on the spatial grid of *I* is calculated as,

$$h_k = \{h_k(h, w) | 1 \leq h \leq H, 1 \leq w \leq W\} \quad (2)$$

Where  $h_k(h, w)$  defines the number of gray-level occurrences of *I<sub>k</sub>* in the spatial grid present in the region of size,  $\left[ \left( (h-1) * \frac{M}{H}, h * \frac{M}{H} \right) \times \left( (w-1) * \frac{N}{W}, w * \frac{N}{W} \right) \right]$ . The total grids number on the 2D SH is *H*\**W* which was estimated vigorously through the aspect ratio,  $r = \frac{M}{N} = \frac{H}{W}$ .

$$W = \left\lfloor \left( \frac{K}{r} \right)^{1/2} \right\rfloor \text{ and } H = \left\lfloor (Kr)^{1/2} \right\rfloor \quad (3)$$

Where the function  $\lfloor \cdot \rfloor$  makes the value round off to its nearest neighbor value.

In the every grid, the distribution of a gray-level *I<sub>k</sub>* can be measured through the spatial entropy and the spatial entropy *S<sub>k</sub>* for a gray-level *I<sub>k</sub>* is obtained according to

$$S_k = - \sum_{h=1}^H \sum_{w=1}^W h_k(h, w) \log_2 h_k(h, w) \quad (4)$$

Further, the obtained spatial distribution has to evaluate with respect to the distributions of the other GLs to know the importance and it is measured through a discrete function *f<sub>k</sub>* as,

$$f_k = S_k / \sum_{l=1, l \neq k}^K S_l \quad (5)$$

Further the obtained discrete function *f<sub>k</sub>* is normalized as,

$$\hat{f}_k = f_k / \sum_{l=1}^K f_l \quad (6)$$

And based on the obtained normalized discrete function  $\hat{f}_k$ , a CDF *F<sub>k</sub>*, of a gray-level *I<sub>k</sub>* is defined as,

$$F_k = \sum_{l=1}^k \hat{f}_l \quad (7)$$

Finally the Contrast Enhanced Gray-level of an output image *O* is attained based on the following mapping criterion

$$O_k = \lfloor F_k(O_u - O_d) + O_d \rfloor \quad (8)$$

The final output *O* denotes the contrast enhanced image. Further the performance of this mechanism is measured through the performance metrics like expected measure of enhancement by gradient (EMEG) and gradient magnitude similarity deviation (GMSD).

#### B. Spatial Correlation based Contrast Enhancement (SCCE)

Though the conventional approach achieved an increased contrast in the output image, this method didn't considered the mutual; correlations between the gray levels, hence, generally, the output contrast enhanced GLs are simply a linear mappings of input GLs, i.e., a particular gray-level in the output image is just linearly related to the input GL and don't have any spatial relationship with the other GLs. In order to address this issue, this work proposes a new contrast enhancement mechanism by considering the spatial relations between the GLs. To obtain a normalized 2D SH, the 2D histogram values are further normalized as



$$h_k(h, w) = h_k(h, w)/HW \quad (9)$$

Such that

$$\sum_{k=1}^K \sum_{h=1}^H \sum_{w=1}^W h_k(h, w) = 1 \quad (10)$$

Here the spatial entropy is measured by evaluating the joint 2D spatial histograms for a given two GLs  $I_k$  and  $I_l$  on the spatial grid found on the area of  $\left[ \left( h * \frac{M}{H}, (h+1) * \frac{M}{H} \right) \times (w * NW, (w+1) * NW) \right]$ , as

$$h_{k,l}(h, w) = \min(h_k(h, w), h_l(h, w)) \quad (11)$$

The above expression gives a new evaluation procedure to measure the spatial relationships between two GLs  $I_k$  and  $I_l$ . Further to obtain the spatial dependencies of GLs and the respective spread over the image spatial domain, a new metric called Spatial Correlation (SC) is derived here and formulated as,

$$SC_{k,l} = \sum_{h=0}^{H-1} \sum_{w=0}^{W-1} h_{k,l}(h, w) \left( \frac{h_{k,l}(h, w)}{h_k(h, w)h_l(h, w)} \right) \quad (12)$$

Where  $SC_{k,l}$  is the spatial correlation between two GLs  $I_k$  and  $I_l$ . The above expression gives a spatial relationship between the GLs  $I_k$  and  $I_l$ . The SC is high when the GLs  $I_k$  and  $I_l$  happen jointly over the nearest spatial areas and the spread over the image spatial domain. Hence, this approach can distribute the GLs in a wide fashion with higher discriminations between the GLs  $O_k$  and  $O_l$  such that the obtained contrast should be high.

After measuring the spatial correlations for every GL in accordance to all other GLs, one rank is assigned to that relation based on the closeness and finally the output gray-level  $O_k$  is obtained through the following mapping function,

$$O_k = \lfloor O_{k-1} + \Delta_{k-1,k}(O_u - O_d) \rfloor \quad (13)$$

Where

$$\Delta_{k-1,k} = \frac{r(k-1) + r(k)}{2} \quad (14)$$

The term  $\Delta_{k-1,k}(O_u - O_d)$  in Eq. (13) is the semantic gap between the output GLs  $O_{k-1}$  and  $O_k$ . This semantic gap is discovered with respect to the mutual contribution of successive GLs that are defined based on their average rankings. The proposed mapping function always ensures that the obtained contrast enhanced GLs range is definitely in between the allowed dynamic range only. Thus the proposed approach efficiently exploits the allowable dynamic range and produces an effective contrast enhanced image.

#### IV. SIMULATION RESULTS

This section describes the details of simulation experiments conducted over the proposed approach through different dental X-ray images. The proposed approach was assessed both quantitatively and qualitatively. Qualitative assessment is mostly apprehensive with visual perception of the contrast enhanced image. But, this is a non-trivial procedure which indirectly be contingent to the human observation. Particularly, in the case of small differences in the contrast. Therefore, the quantitative assessment is performed additionally based on the objective evaluations on the contrast enhanced images.

##### A. Qualitative Assessment

In the case of qualitative assessment, the performance of proposed mechanism is observed by human observer. To

show the performance enhancement with respect to the qualitative assessment, several images are processed through the developed mechanism and the obtained results are depicted in this section. Moreover to compare the proposed method with conventional approaches, the test imagery was also processed through conventional approaches for contrast enhancement. The conventional approaches considered here for comparison are namely, CLAHE [16], Histogram Registration (HR) [13], and Contrast Stretching (CS) [18]. The obtained contrast adjusted images of different dental x-ray images are shown below.

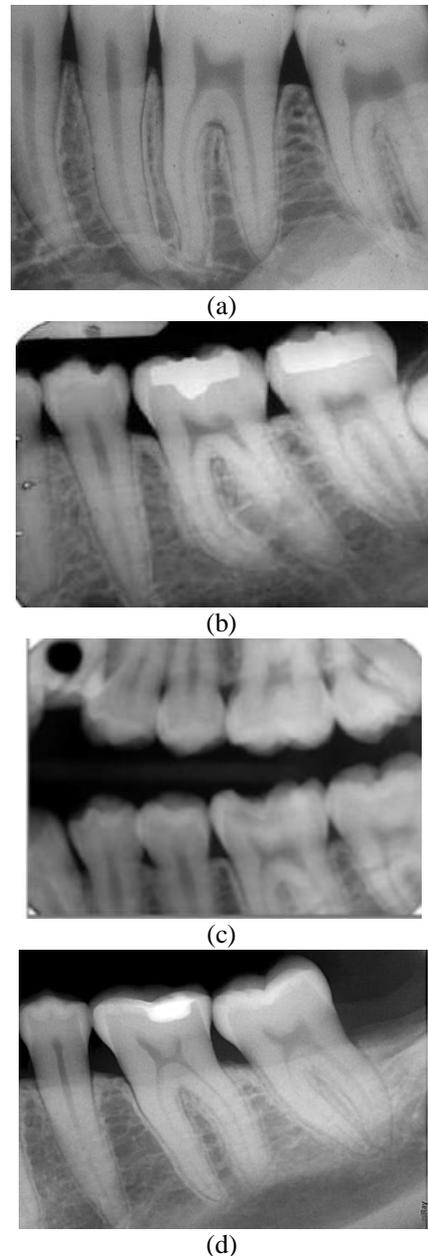
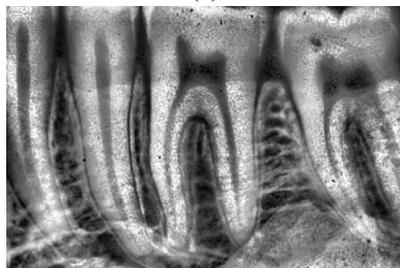


Figure.1 Test Images of dental radiographs



(a)



(b)



(c)

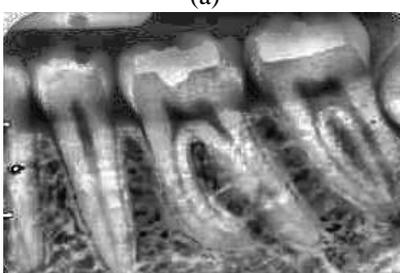


(d)

Figure.2 Obtained results for test image (figure.1a) through, (a) CLAHE, (b) Histogram Registration, (c) Contrast Stretching and (d) Proposed Approach



(a)



(b)

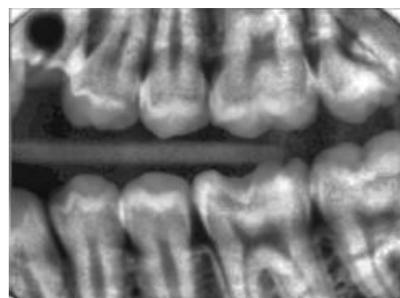


(c)

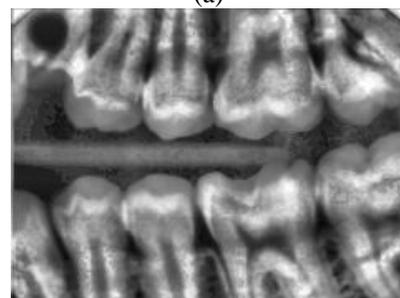


(d)

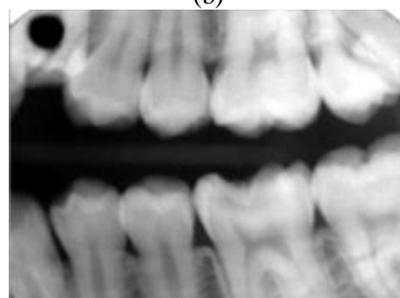
Figure.3 Obtained results for test image (figure.1b) through, (a) CLAHE, (b) Histogram Registration, (c) Contrast Stretching and (d) Proposed Approach



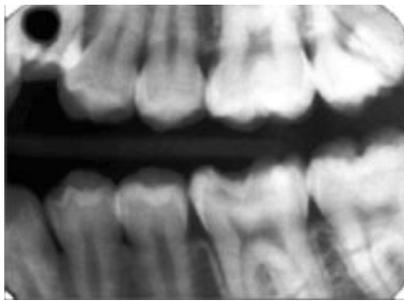
(a)



(b)



(c)



(d)

Figure.4 Obtained results for test image (figure.1c) through, (a) CLAHE, (b) Histogram Registration, (c) Contrast Stretching and (d) Proposed Approach



(a)



(b)



(c)



(d)

Figure.5 Obtained results for test image (figure.1d) through, (a) CLAHE, (b) Histogram Registration, (c) Contrast Stretching and (d) Proposed Approach

B. Quantitative Assessment

The performance metric used here is “contrast root mean square difference (CRMSD)”. CRMSD is an adaption of the

conventional “root mean square deviation (RMSD)”, generally used to evaluate the performance with respect to the deviation between two pixels [28]. In this case, the pixel values form two images considered, one is original image and another is contrast enhanced image. For a given image of width N and height M, the CRMSD is defined as;

$$CRMSD = \sqrt{\frac{\sum_{m=0}^M \sum_{n=0}^N (E(m,n) - O(m,n))^2}{M \cdot N}} \quad (15)$$

Where  $O(m,n)$  and  $E(m,n)$  are the contrast of single pixels with coordinates  $(m,n)$  from the original and enhanced images respectively. The particular quantities can be obtained through the following equation.

$$O(m,n) = \frac{lv(m,n)}{lm(m,n)} \quad (16)$$

For each pixel  $(m,n)$ , of image  $I(m,n)$ , the quantities can be evaluated according to the following equations.

$$lm(m,n) = \frac{1}{(2m+1)^2} \sum_{k=-m}^m \sum_{l=-m}^m I(m+k, n+l) \quad (17)$$

$$lv(m,n) = \frac{1}{(2m+1)^2} \sum_{k=-m}^m \sum_{l=-m}^m (I(m+k, n+l) - lm(m,n))^2 \quad (18)$$

Where  $I(m+k, n+l)$  is the pixel intensity in the coordinates  $(m+k, n+l)$  and  $(2m+1)^2$  is a constant which determines the square block size through the pixels. In the present scenario, it is considered as  $3 \times 3$ . The obtained CRMSD details for all the above test imagery is represented in the following table.1.

Table.1 Obtained CRMSD for Test Imagery

	Image 1	Image 2	Image 3	Image 4
Original	0.997	0.820	0.686	0.882
CLAHE [16]	0.954	0.768	0.633	0.812
Histogram Registration [13]	0.887	0.722	0.587	0.770
Contrast Stretching [18]	0.852	0.709	0.559	0.754
Proposed	<b>0.811</b>	<b>0.681</b>	<b>0.517</b>	<b>0.719</b>

As described in the table.1, the obtained CRMSD values are more far from the original CRMSD values for every test image. Further it can also be observed that the proposed approach has attained a much improvement in the contrast of test imagery when compared the conventional approaches. From the above both qualitative and quantitative assessments, it is proved that the proposed contrast enhancement mechanism can improve the contrast of any type of image.

V. CONCLUSIONS

A new quality improvement mechanism is proposed in this



paper to enhance the quality of low contrast dental radiographs such that they can be processed for efficient dental diseases diagnosis. Since the approximation of proper grey levels is most important for an automatic diagnosis system accomplishing through digital image processing techniques, this paper tried to improve the contrast levels of a low contrast dental radiographs such that making the image more informative and effective. The proposed method considered the spatial correlations between the pixels of image for contrast enhancement of neighboring pixels. The obtained simulation results proved the performance effectiveness of proposed method through both quantitative and qualitative assessments.

### REFERENCES

1. Kumar, 2011. Extraoralperiapical radiography: an alternative approach to intraoral periapical radiography. *Imag. Sci. Dent.* 41, 161–165.
2. Lai, Y.H., Lin, P.L., 2008. Effective segmentation for dental x-ray images using texture-based fuzzy inference system. *Adv. Concepts Intell. Vis. Syst. Lect. Notes Comput. Sci.* 5259, 936–947.
3. Rad, A.E., 2013. Digital dental X-ray image segmentation and feature extraction. *TELKOMNIKA* 11, 3109–3114.
4. Nikneshan, S., 2015. The effect of emboss enhancement on reliability of landmark identification in digital lateral cephalometric images. *Iran. J. Radiol.* 12, e19302.
5. Zhou, J. Abdel-Mottaleb, M., 2005. A content-based system for human identification based on bitewing dental X-ray images. *Pattern Recognit.* 38, 2132–2142.
6. Lpez-Lpez, J., 2012. Computer-aided system for morphometric mandibular index computation (using dental panoramic radiographs). *Med. Oral Patol. Oral* 17, e624–e632.
7. Nakamoto, T., 2008. A computer-aided diagnosis system to screen for osteoporosis using dental panoramic radiographs. *Dentomaxillofacial Radiol.* 37, 274–281.
8. Wriedt, S., 2012. Impacted upper canines: examination and treatment proposal based on 3d versus 2d diagnosis. *J. Orofac. Orthop.* 73, 28–40.
9. M. Sakata and K. Ogawapp, "Noise Reduction and contrastenhancement for small-dose X-ray images in wavelet domain," presented at the Nuclear Science Symposium Conference record(NSS/MIC), 2009.
10. R. Aufrichtig and P. Xue, "Dose efficiency and low-contrastdetectability of an amorphous silicon x-ray detector for digitalradiography," *Phys. Med. Biol.*, vol. 45, pp. 2653–2669, 2000.
11. M. Mehdizadeh and S. Dolatyar, "Study of Effect of AdaptiveHistogram Equalization on Image Quality in Digital Preapical Image inPre Apex Area", research *Journal of Biological Science*, pp: 922 – 924, vol: 4, issue: 8, 2009.
12. M. Sakata and K. Ogawapp, "Noise Reduction and contrastenhancement for small-dose X-ray images in wavelet domain," presented at the Nuclear Science Symposium Conference record(NSS/MIC), 2009.
13. TL Economopoulos, PA Asvestas, GK Matsopoulos, K Gro'ndahl and H-G Gro'ndahl, "A contrast correction method for dental images based on histogram registration", Technical Report, *Dentomaxillofacial Radiology* (2010) 39, 300–313.
14. M. H. A. Hijazi, F. Coenen, and Y. Zheng, "Retinal image classification using a histogram based approach," in *Proc. of Int. Joint Conf. on Neural Networks*, pp. 1–7, Barcelona (2010).
15. Wang, Q., & Ward, R. K. (2007). Fast image/video contrast enhancement based on weighted thresholded histogram equalization. *IEEE transactions on Consumer Electronics*, 53(2), 757-764.
16. A. W. Setiawan, T. R. Mengko, O. S. Santoso, and A. B. Suksmono, "Color retinal image enhancement using CLAHE," in *Proceedings of the International Conference on ICT for Smart Society (ICISS '13)*, pp. 1–3, Jakarta, Indonesia, June 2013.
17. SitiArpahBt Ahmad, "The effect of sharp contrast-limited adaptive histogram equalization (SCLAHE) on Intra-oral dental radiograph images", *IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, 2010.
18. Haris B Widodo, AriefSoelaiman, Yogi Ramadhani and RetnoSupriyanti, "Calculating Contrast Stretching Variables in Order to Improve Dental Radiology Image Quality", *IOP Conference Series: Materials Science and Engineering*, Volume 105, 2016.
19. SitiArpah Ahmad, MohdNasirTaib, Noor ElaizaA.Khalid, Rohana Ahmad, HaslinaTaib, " A comparison of image enhancement techniques for dental x-ray image interpretation", *GCSE 2011: 28-30 December 2011*, Dubai, UAE.
20. TurgayCelik, "Spatial Entropy-Based Global and Local Image Contrast Enhancement", *IEEE Transactions On Image Processing*, Vol. 23, No. 12, December 2014.