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A Review on Methods of Enhancement And Denoising in Retinal Fundus Images

P.S. Bindhya[1*], R. Chitra[2], V.S. Bibin Raj[3]

[1]Department of Computer Science and Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, Tamil Nadu, India
[2]Department of Computer Science and Engineering, NICHE, Kumaracoil, Tamil Nadu, India
[3]Department of Electrical and Electronics Engineering, Heera College of Engineering and Technology, Kerala, India

**Corresponding Author: bindhyabibin@gmail.com, Tel.: +91-94968-15506*

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Abstract— Diabetic Retinopathy (DR) is a disease caused by abnormalities in blood vessels in the eyes. DR can be detected in the early stages by the Detection of Micro Aneurysms in fundus retinal images. Retinal fundus pictures are commonly used for finding and analysis of DR disease that help ophthalmologists to complete the evaluation of retinal diseases. By reduction in noise level and by enhancing some features in the image pre-processing techniques are adopted. Restoration of images is done to happen by numerous pre-processing techniques. Here in this paper, the comparison of pre-processing in the retinal fundus image is done. For the precise visual view of DR-related highlights, the nature of fundus pictures should be enhanced to a satisfactory level. The difference is a more critical quality than a unique degree of splendor and goals. The main purpose of the pre-processing technique is to increase the diagnostic possibility in fundus images for visual assessment and also for computer-aided segmentation. This paper deals with the comparison of different retinal image denoising technique and their parameters such as MSE, PSNR, Correlation coefficient, RMS values, etc were reviewed and compared with different datasets for retinal images in connection with the identification of DR and Micro Aneurysms (MA).

Keywords— Spatial Domain filtering; Contrast Enhancement; Vessel enhancement.

I. INTRODUCTION

DR is an ailment that makes misfortune the vision. The recognition of the beginning period of DR can help the individuals from whole vision misfortune. Veins in the retina source blood and oxygen to the retina. If the oxygen supplies in the retina are not even, at that point this makes medical issues like hypertension, cardiac issues [1]. It influences up to 80 % of individuals who have had diabetes for a long time or more. The fundus picture comprises of the retina, optic circle, fovea, macula, and it is inverse to a focal point. For fundus photography, a magnifying lens joined flashed camera is utilized. The morphology of the retinal fundus picture is a significant pointer of sicknesses like DR, hemorrhages, hypertension, vein occlusion, and glaucoma [2]. The early signs of DR are Micro aneurysms (MAs), so there is a need of detecting this lesion. The MAs are appearing in small circular shady spots on the outside of the retina [3]. At the point when the sugar level in blood expands, at that point, it builds the receptive oxygen in the blood. It costs the retinal vascular tree and mains to the development of lesions in the retina. The detection of MAs is hard because it is not easy to distinguish them from certain parts of the vascular system. Mostly MA appears near thin vessels. If the diagnosis of DR is made early then it can be treated with help of available methods. The nearness of injuries in the retina is the underlying indication of DR [4][12]. The fundamental square chart for picture handling takes seemed in figure 1.

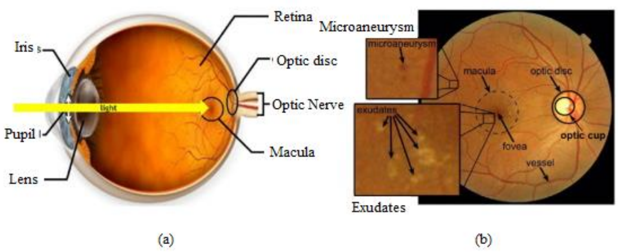

Figure 1. Retinal fundus image, where (a) structure of the human eye; (b) Fundus image with signs of DR [24]

The most widely recognized indications of DR are red sores and splendid injuries. Small scale aneurysms and exudates are red injuries, and cotton fleece acnes are splendid sores in the retina. The nearness of a red sore is the early indication of DR. Small scale aneurysms show up as red dots in retinal fundus pictures. Splendid injuries happen subsequently from the breakdown of blood from the retinal hindrance [5][15]. Morphological changes like measurement, stretching edge, length happen in retinal veins. A variety of these highlights changes in retinal vessels is the principal side effect of DR.

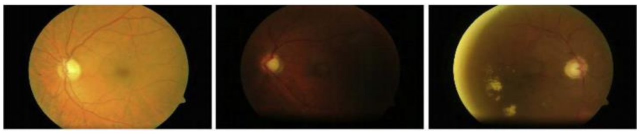

Figure 2. Varying Illumination on Fundus Images (a) Bright illumination (b) Poor illumination (c) Crescent artifacts occurred during image acquisition

The unconstrained retinal guide is utilized for the macular debilitating treatment. Based on the considerable number of requests for the extraction of retinal veins, there is a necessity for a specific retinal vein extraction structure[16].

To identify different methods adopted for the analysis of blood vessels under DR, a detailed review is all necessary. Here it describes some of the real challenges faced by the researchers in the area of image processing and enhancement of retinal images. The detailed literature has been done regarding the DR, MA's with different pre-processing techniques and some challenges in section II. Section III details the different methods and schemes for pre-processing, especially for noise removal. Section IV describes some of the performance parameters and their empirical forms. Section V details the conclusion, recommendation of selected methods, and future scope

II. RELATED WORK

In the Retinal fundus, descriptions provide a non-invasive conception of the retinal vessel construction. Applying image dispensation techniques in the study of digital color fundus shots and analyzing their vasculature is a reliable line for early diagnosis of the above-mentioned diseases. Signs of DR include red grazes such as MA, intra-retinal hemorrhages, and bright lesions, such as cotton wool spots and exudates.

Two interesting factors are low disparity of the fundus images and inhomogeneous lighting of the related images as discussed in [31]. Inhomogeneous illumination is caused by imaging development, while low contrast is the result of the fact that dissimilar blood vessels have different dissimilarity with the background. In other words, denser vessels have higher contrast in assessment to thinner ones. Also, variations in the color of the retina for diverse subjects that originate from biological features raise another delinquent.

Commonly faced difficulties such as varied decorations, high/low contrast, brightly or poorly lit, and creating a standard single discovery method is hard as in [19]. The noise during the image attainment process may lead to false recognition of the object of interest. The presence of some positive and dusky pixels around the optic disc frontier can hamper precise boundary dissection. The presence of body fluid vessels in the layers lower the retina can be seen in the fundus metaphors because of the skin coloring.There is a wide difference in the color of the retina from patient to patient as well [31]. Thus the images need to be gutted and process-able.

In [32] explored that the occurrence of lesions may be mis-enhanced and mis-detected as blood vessels. The dissection of the thinner vessels is problematic as the image distinction is generally low around thin vessels. If the image class is not good the vital reflex often disappears as illustrated in [33]. The vessels in the external regions of the image are very dusky due to the screening effect. The thickness of the vessel is also not very valuable for arrangement, since its variations being main near the optic disk and the smallest on the outside parts of the image.

The significant preliminaries in red sore finding is expressed in [34]. The division of little MA in the regions of low picture differentiate and the event of brilliant pathologies. As brilliant sores have sharp edges, little "islands" of the typical retina are shaped between them, when they lie near one another. These can be false positives. The unconstrained retinal guide is utilized for the macular debilitating treatment. Based on the considerable number of requests for the extraction of retinal veins, there is a necessity for a specific retinal vein extraction structure. To identify different methods adopted for the analysis of blood vessels under DR, a detailed review is all necessary. Here it describes some of the real challenges faced by the researchers in the area of image processing and enhancement of retinal images [16]

- Flat regions ought to be smooth.
- Edges ought to be secured without obscuring.
- Textures ought to be protected.
- New ancient rarities ought not to be produced.

III. METHODOLOGY

Pictures might be adulterated with noise during its obtaining and transmission appeared in figure 2(c). Likewise, the commotions may emerge because of the movement of the camera or the movement of the item itself. Picture reclamation endeavors to evacuate these commotions in the pictures while attempting to save however much as highlights as could reasonably be expected. So, in fundus image processing, the first step is to evaluate the noise in the image, then to estimate noise type. Various types of noises are Gaussian noise, Speckle noise, salt and pepper noise, Brownian noise, and Poisson noise. Among them, Gaussian noises and Salt and pepper noise are the main noises that affect the retina fundus image.

Generally, there are two types of noise models such as additive and multiplicative noise models. The measured model for additive noise model is detailed in (1).

$$N(x,y) = I(x,y) + J(x,y) \tag{1}$$

$$N(x,y) = I(x,y) \times J(x,y) \tag{2}$$

Equation (2) details the multiplicative noise, Where $N(x,y)$ is the original noisy image, $I(x,y)$ is the original noise-free image $J(x,y)$ is the noise present in the image $I(x,y)$. The image denoising techniques mainly concentrate on the emission of noise $J(x,y)$ and help to reconstruct the form

$I(x, y)$ by retaining all the key features of the creative image. Normally Gaussian noise and salt and pepper noise derive under additive noise models and speckle noise derives under multiplicative noise. Additive noises stand easier to eradicate than multiplicative noises.

Gaussian noise occurs during data acquisition. It is evenly distributed such that each pixel in the raucous image is the totality of the arbitrary Gaussian noise value and accurate pixel value. In it, the distinction of intensity value is with the gaussian normal dispersal occur. This noise is self-determining of each pixel and is self-governing of signal strength. The density distribution function is given in the following (3) with a grey level of 'n', noise variance σ^2, and 'm' the mean value.

$$F(n) = 1/\sqrt{(〖2\pi\sigma〗 ^2)} \cdot e^{(〖(n-m)〗 ^2/ (2\sigma^2))} \quad (3)$$

Salt and pepper noise likewise called level tail disseminated or motivation commotion. A picture influenced by salt and pepper commotion has dull pixels in the brilliant locales and splendid pixels in the obscurity area. Salt and pepper disorder is a motivation kind of noise, which is likewise alluded to as power spikes. For an 8-piece picture, the estimation of pepper commotion is 0, and salt noise is 255. Salt and pepper noise is, for the most part, brought about by the breaking down of pixel components in the sensors of cameras, broken memory areas, or timing mistakes of the digitization procedure. The principle wellspring of salt and pepper noise is because of the mistakes in ADC and because of the bit in the program as in [6]. The Probability Density Function with P_a, P_b represents the probability of samples 'a' and 'b' respectively for n number of random variables is discussed below in (4). Speckle noise stands as a kind of multiplicative noise and it is mostly existing trendy ultrasound imageries and SAR (Synthetic Aperture Radar) picture.

$$f(n) = \begin{cases} P_a, \ for\ n = a \\ P_b, \ for\ n = b \\ 0 \quad otherwise \end{cases} \quad (4)$$

A. Pre-Processing Techniques

There are various methods available for removing noises in the image. It depends on the following factors.

- Cost of Computation
- Operating time
- Removal of Noise
- The intensity of the detailed image.

Pre-processing of images can be done through spatial filtering techniques, Vessel enhancement techniques, Contrast enhancement techniques are shown in figure 3. Spatial domain filters enhance the appearance of the image. It is designed to highlight or conquer the precise features in the image based on their spatial frequency. Spatial filtering techniques are classified into linear and nonlinear methods. In the first technique, the calculation can smear straight to all pixels deprived of characterizing the picture corrupted or uncorrupted. They tend to blur the images. In a nonlinear technique, the calculation can just apply pixels by characterizing which pixels are tainted or unaffected. At that point, debased pictures separated by a particular calculation, and no progressions to uncorrupted. The nonlinear filter creates better outcomes contrasted with the direct filter.

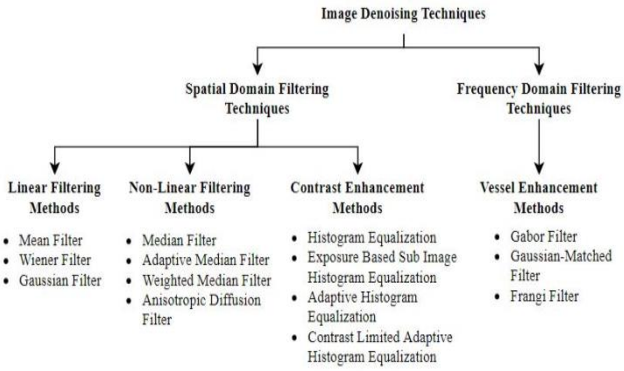

Figure 3. Retinal Image Denoising Classification

B. Spatial Domain filtering

1. Linear Filters:

Linear filters were embraced to evacuate noise in the spatial space, yet they neglect to save picture surfaces. Table. 1 shows a comparison of Linear filters.

a) Mean filter:

The Average (mean) filter smooths picture information, along these lines wiping out the disturbances. This filter achieves spatial filtering by figuring the whole of all pixels in the mesh window and afterward partitions the total by the number of pixels in the filter space. Mean filtering in [11] has been received for Gaussian noise decrease; be that as it may, it can over-smooth pictures with high noise. The mean filter is computed in (5) as,

$$g(x, y) = \frac{1}{MN} \sum f(x, y) \quad (5)$$

$g(x, y)$ is the mean data as in [2].

b) Wiener filter:

Wiener filter is a factual methodology that lessens the measure of noise in a picture through an estimation of the ideal noiseless picture. It is the mean squares blunder ideal stationary linear filter for pictures corrupted by added substance noise and obscuring. It is normally applied in the frequency domain as [13], because of linear movement. From (6), Wiener Filter in the Fourier Domain as

$$f(u, v) = \left[\frac{H(u,v)^* P_S(u,v)}{|H(u,v)|^2 \ P_S(u,v) + P_n(u,v)}\right] g(u, v) \quad (6)$$

Where H(u,v) is the Fourier change esteem, $H(u, v)^*$ is the unpredictable conjugate, g (u, v) is the debased image, $P_s(x, y)$ is the force range of sign and $P_n(x, y)$ is the force range of noise[14]. The filter can stifle frequency segments that have been corrupted by noise yet don't ready to remake them. Additionally, it can't fix obscuring brought about by band-constraining of $H(x, y)$.

c) Gaussian filter:

The Gaussian Smoothing executes the normal benefit of neighboring pixels dependent on the Gaussian capacity. This expels the impact of noise and different enlightenments. It goes about as a Gaussian LPF expel HF parts in images. The Gaussian capacity is expressed as,

$$G(x,y) = \frac{1}{2\pi\sigma^2} \cdot e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)} \quad (7)$$

In (7), the estimation of 'σ ' influences contrarily to filtering. This is actualized on each pixel in the picture utilizing the convolution operation. The level of blurring is constrained by the σ or blurring coefficient, just as the size of the kernel utilized by [17]. As loads of a Gaussian filter rely upon the spatial separation may lose picture edges and can present blurring impact, which will make it not reasonable for vessel identification in retinal pictures.

Table 1. Comparison of Linear Filters

Linear filters	**Strength**	**Weakness**
Mean Filter	The simple filter removes impulse noise	Does not preserve the details in the image
Wiener Filter	Reduces mean square error.	Smoothen the image will blur the resultant image.
Gaussian Filter	Viable in dispensing with Gaussian noise	Requires some more time and subtleties may be lost.

2. Non-Linear Filters:

Non-linear filtering is done in two stages. During the principal stage, recognizes the pixel as undermined or uncorrupted and during the subsequent stage, the pixel that is defiled is sifted without changing the uncorrupted pixel esteem as in [22]. Table 2 shows a comparison of Non-Linear filters.

a) Median Filter:

A median filter is a non-linear smoothing method to expel salt and pepper noise. This is superior to the mean filter, the medians are the center estimation of the local pixel. The median filter keeps the perceptiveness of picture boundaries while expelling noise. The disadvantages are, it evacuates the two noises and subtleties as it can't comprehend careful subtleties from noises by [8].

b) Adaptive Median Filter [AMF]:

On account of the AMF arranges the pixel in the picture by its encompassing neighbor pixel; the size of the neighbor pixels are customizable. It evacuates motivation noises, decreases twists, and over the top diminishing and thickening of limits in [8]. The motivation noise pixels are supplanted by the median pixel estimation of the pixels in the local that have finished the disturbance characterization assessment.

c) Weighted Median Filter:

The filtering operation of the weighted median filter is controlled with the lower and upper filter limits which are utilized to decide the exchange off among noise and detail protection. It doesn't give better de-noising results when the noise is 30% or more. The principal reason is that during the procedure it demolishes some auxiliary and spatial neighborhood data in [22]. Along these lines, to beat this disadvantage, AWMF is utilized.

d) Adaptive Weighted Median Filter [AWMF]:

The AWMF median filter dispenses with noise and jam the edges of the vein simultaneously. It adaptively decides the heaviness of every pixel in the filter window and denoises the picture in a limited capacity to focus. Diffusion is an iterative procedure that follows a schedule.

Table 2. Comparison of Non-linear filters.

Non-linear filters	**Strength**	**Weakness**
MF	Removes salt and pepper noise, Preserve edges	Removes both the noise and the fine details. It is corrupted by Gaussian noise
AMF	Performs well at low noise densities.	Window size should be increased at high noise density which will blur the image.
WMF	Focus on edge preservation	Destroys structural and spatial neighborhood information when noise is more than 30%.
AiDF	Smooth the images within homogeneous regions	Blur vessel boundaries

e) Anisotropic Diffusion Filter [AiDF]:

AiDF is a form of non-linear filter to utilize neighboring pixels for noise expulsion from pictures. It changes the filter imperatives to diminish the diffusion on the limits and to play out a couple of emphasis for blurring homogeneous areas. Consequently, it smoothens the picture while jam edge powers are identified with the vessels by [17]. A 3×3 anisotropic diffusion cover utilizes eight neighboring pixels.

f) Complex Shock Filter:

A complex shock filter is a non-direct forward-in reverse dispersion-based methodology for the enhancement of images. It expels dot noise. It just upgrades edges and not right for any complexity float. It lessens irregular changes and smothers JPEG artifacts by prompting a superior SNR after upgrade in [28].

$$\begin{array}{ccc} P_{NW} & P_N & P_{NE} \\ P_W & P & P_E \\ P_{SW} & P_S & P_{SE} \end{array}$$

Figure 4. 3 × 3 Anisotropic Diffusion Mask

Figure.4 shows, for a pixel P, the P_N, P_S, P_W, P_E, P_{NW}, P_{NE}, P_{SW}, P_{SE} indicates the neighborhood pixels by [23]. Anisotropic noise suppression encompasses the calculation of the divergence of the sum of the Laplacian and the gradient of the image.

g) COSFIRE filters:

The COSFIRE filters are processed as the weighted geometric mean of masked and shifted Gabor filter reactions. They are flexible key point finders as they can be arranged with some random nearby contour pattern and are in this way ready to distinguish the equivalent and comparable examples. The filter contrast from other bifurcation location approaches in two primary viewpoints. Initially, in contrast with skeleton-based methodologies, the technique is increasingly powerful for the recognition of deficient intersections that are regularly erroneously created via programmed division calculations. Second, a COSFIRE filter is trainable as it is designed with any nearby example that is indicated by a client [29].

3. Enhancement Methods

Image enhancement is the way toward expanding the nature of the power varieties in the image. Differentiation is made by the distinction in luminance reflected from two contiguous surfaces. In visual recognition, differentiation is dictated by the distinction in the shading and splendor of an article with other objects by [25][26].

a) Histogram Equalization (HE) :

HE centers around the force of the image to upgrade the neighborhood differentiation of the image. It chips away at the standard of a consistently disseminated grayscale histogram. On the off chance that the image histogram has a level and wide dim level, it speaks to a high complexity image. It is reasonable for light foundation and dim frontal area images. It extends nearby difference to get the non-obvious image include. In any case, it has a downside that the image isn't balanced consistently in [7].

b) Exposure Based Sub Image Histogram Equalization (ESIHE)

ESIHE is utilized for the differentiation improvement of low introduction grayscale image by [27]. It depends on the tallness of the histogram. It cuts the most elevated histogram esteem as opposed to the predefined limit esteem. It can change the cut-out edge esteem. It is powerful as far as entropy and differentiation for low greyscale images.

c) Adaptive Histogram Equalization (AHE):

AHE technique registers various histograms and each compared to a specific piece of the subject and redistributes the delicacy estimations of the subject. It is principally reasonable for improving the meanings of edges in every district of an identified subject. The differentiation among foundation pixels and their data prompts the improvement of the boisterous pixels in AHE. The profiled pixels show up as foundation data [10].

d) Contrast Limited Adaptive Histogram Equalizations.

In CLAHE, the image is partitioned into little districts called tiles. The histogram of each tile is balanced so nearby differentiation is upgraded. This technique utilizes a complexity constrained change work on encompassing neighborhood pixels to improve the differentiation [21]. For the confinement of the unmistakable quality of noise in the image, cut factor worth will be set. It will choose the change in processed worth. In figure 5, CLAHE applies to the green component filtered image. The force segment is improved by Rayleigh change in Contrast Limited Adaptive Histogram Equalization (Rayleigh CLAHE). In Rayleigh CLAHE, it keeps a decent differentiation of veins just as jam chromatic data in the retinal picture.

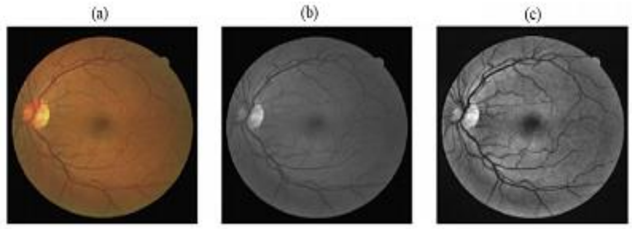

Figure 5. (a) Original retinal image, (b) Extracted green filter image, (c) Contrast limited adaptive histogram equalized image in [19]

Accordingly, it improves the general appearance by [18].

The qualities of retinal blood vessels with length, width, tortuosity, branching pattern, and angles will underwrite the analytical result in [29]. Gaussian filter is utilized to obscure pictures and expel noise. It additionally improves the vascular example particularly flimsy, less noticeable vessel, smoothens the foundation, and disposes of the non-vessel pixels by [24].

C. Frequency domain filtering Techniques

1. Gaussian-Matched Filter:

It is the 2D Gaussian built coordinated filtering utilized for the explanation that the cross-sectional vessel outline is like a Gaussian shape. A 2D Gaussian-based coordinating format is used for the best guess to the veins. The scientific condition of a 2D Gaussian format is given as in (8) [15],

$$G(x,y) = -exp\left(\frac{x^2+y^2}{2\sigma^2}\right) \quad (8)$$

In the Matcher filter, each coefficient is calculated as,

$$K_\theta(x,y) = -exp\left(\frac{-u^2}{2\sigma^2}\right), \qquad \forall P_\theta \in N \quad (8.\alpha)$$

$$P_\theta = [u,v] = [x,y]\begin{bmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix} \quad (9)$$

Where $N = \{(u,v): |u| \le T, |v| \le {}^{L}/_{2}\}$, T is the site of the gaussian arch tracks, L is the span of the vessel part of one alignment and u is the strength, P is a point in the neighborhood N and θ is the orientation of the filters kernel by [30].

2. Gabor filters:

Gabor Filters are generally used for surface upgrade and highlight extraction in the picture. An intricate Gabor function is developed by increasing a Gaussian cover function with a composite trigonometric function. The genuine piece of a two-dimensional Gabor kernel function is utilized to improve retinal veins. The 2D Gabor kernel function is given as in (10),

$$g(x, y; \lambda, \theta, \sigma, \gamma) = exp\left(-\frac{\acute{x}^2+\gamma^2\acute{y}^2}{2\sigma^2}\right) cos\left(2\pi\frac{\acute{x}}{\lambda}\right) \quad (10)$$

Where g is the two dimensional Gabor kernel function, $\acute{x} = xcos\theta + ysin\theta$ and $\acute{y} = -xsin\theta + ycos\theta$ where σ, θ, λ, γ defines standard deviation, orientation, wavelength, and aspect ratio. Accordingly, the pixels have a place with the retinal veins which are increasingly predominant contrasted with foundation pixels in [9].

3. Frangi Filter:
Frangi filter utilizes Hessian Eigen's put together methodology concerning the high lift filtered picture for the vessel balance improvement alongside concealment of the non-vascular edifice of varied and dainty vessels. The Hessian grid is processed by calculating the second request subordinate of a picture in the x-axis, y-axis, and both diagonals of right and left.

4. Vesselness Filter:
The vesselness filter is used to notice blob edifices in an image. A vesselness filter dependent on Hessian is depicted in [25] as (11)

$$F(x) = max_\sigma f(x, \sigma) \quad (11)$$

where x is a position of a pixel in an image; f is the filter applied for vessel finding and σ is the standard deviation for calculating Gaussian image imitative. The Hessian matrix is given below with the second partial derivatives parameters as I_{xx}, I_{xy}, I_{yx} and I_{yy} to maintain the image intensity.

$$H = \begin{bmatrix} I_{11} & I_{12} \\ I_{21} & I_{22} \end{bmatrix} = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{bmatrix} \quad (12)$$

From the derivative, λ_1 and λ_2 are calculated and ordered as $\lambda_1 < \lambda_2$. Then, a likelihood value is gained according to V(s) role for each pixel (13).

$$V(s) = f(x) = \begin{cases} 0, & \lambda_2 > 0 \\ exp\left(-\frac{R_B{}^2}{2\beta^2}\right)\left(1 - exp\left(\frac{S^2}{2c^2}\right)\right), & \lambda_2 \le 0 \end{cases} \quad (13)$$

Where $R_B = \frac{|\lambda_1|}{|\lambda_2|}$ and $S = \sqrt{\lambda_1{}^2 + \lambda_2{}^2}$
β, c is used to arrange the sensitivity of R_B , S values correspondingly. The improved image V is obtained at diverse scales, S using values 1.5 and 4.5 The extreme reply of all V (s) standards are certain for each pixel. The output is detailed as in the figure. 6.

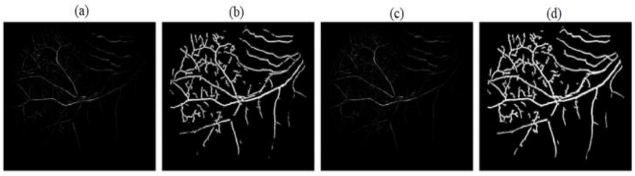

Figure 6. Analysis of vessel enhancement in STARE dataset using Frangi filter. (a) Enhanced thin vessel image (b) Thin binary image (c) Enhanced thick vessel image (d) Thick binary image [25]

5. Self-Adaptive Matched Filter [SAMF]:
SAMF utilizes a non-direct synergistic blend of the vesselness filter and the matched filter for the identification of retinal veins. It is planned from the direction histogram of the yield of the vesselness filter. This is accomplished by assessing the parameters of the coordinated filter part by separating significant data present in the direction histogram by [30].

IV. PERFORMANCE EVALUATION

The exhibition of different strategies is looked at utilizing execution assessment measurements, for example, PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error).

1. MSE:
MSE is utilized to assess the contrast between the first worth and the worth suggested by a filter. Consider the info Image size M x N pixels. The numerical (14) for MSE in [13] is given as,

$$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(X_{jk} - Y_{jk}\right)^2 \quad (14)$$

where x_{jk} is the original input image at the location $(_{j,k})$ and Y_{jk} denotes the reconstructed image at the location $(_{j,k})$. After calculated the MSE value as shown in figure 7, it is applied to get a PSNR value.

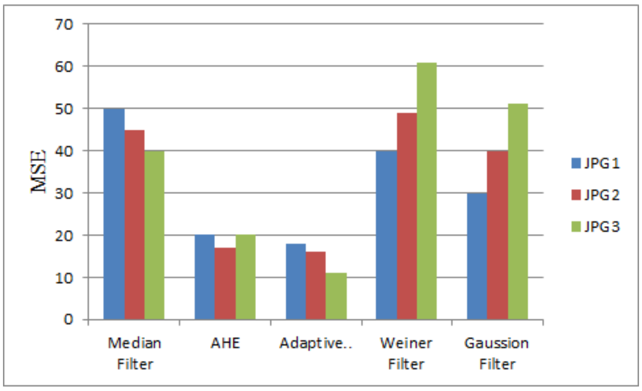

Figure 7. Evaluation of different pre-processing algorithms by MSE

2. PSNR:
PSNR means to show the nature of the resultant picture. It is the proportion between the maximum conceivable worth and the estimation of the noise in the picture. A more prominent PSNR esteem shows the high quality of the

remade picture. What's more, the Eqn. for PSNR is given by (15), Peak value specifies the maximum alteration between the input image rate and PSNR are detailed in figure 8 as in [8][21].

$$PSNR = 10\log\frac{(Peakvalue)^2}{MSE} \quad (15)$$

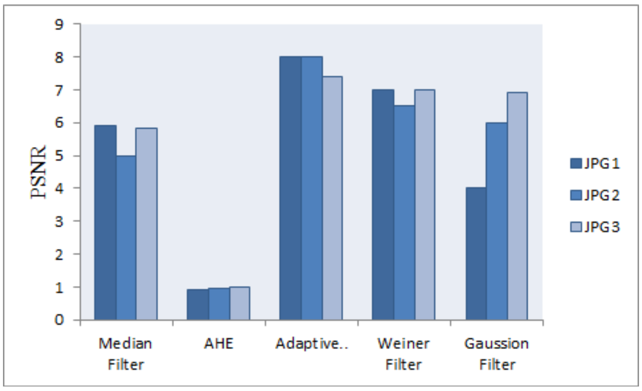

Figure 8. Evaluation of different pre-processing algorithms by PSNR

3. Entropy:

Entropy evaluates the normal content info of the image. The larger the value of entropy, the image quality will be better. The entropy as in [26] of the image 'I' is defined as in (16)

$$H(I) = -\sum_{i=1}^{M} P(x_i)log_2 P(x_i) \quad (16)$$

Where x_i denotes the intensity value of I, M denotes maximum intensity value and $P(x_i)$ is the probability function of x_i. If the entropy of the restored image is higher than the original image means that the restored image takes more information than the unique image[31].

4. Structural Similarity Index:

Structural Similarity Index (SSIM) is a measurable amount to evaluate picture quality. It quantifies the comparison of the improved picture and the first picture. If the estimation of SSIM is higher methods the pictures are structurally indistinguishable. For the given two pictures x and y, SSIM is expressed as in the following (17)

$$SSIM\ (x, y) = \left[l(x, y)^{\alpha} \cdot c(x, y)^{\beta} \cdot s(x, y)^{\gamma}\right] \quad (17)$$

Where α, β, γ are the weights assigned for luminance (l), structure (s) and contrast (c).

The Luminance function, Contrast function, Structure-function is computed as defined in (18),(19), and (20).

$$l(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \quad (18)$$

$$c(x, y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \quad (19)$$

$$s(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \quad (20)$$

Where μ_x is the average of x, μ_y is the average of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y and σ_{xy} is the covariance of x and y. c_1 and c_2 are the two parameters which are used to even the division operation with unfortunate denominator and $c_3 = \frac{c_2}{2}$. As in [20] if there are perfect similarity SSIM approaches to 1.

5. Correlation Coefficient (CoC):

Correlation Coefficient (CoC) is utilized to quantify the chromatic data. It quantifies the quality of the direct relationship between two pictures X and Y. The worth ranges between - 1 to 1 contingent upon the similarity of x and y as detailed in [18]. CoC is expressed as in (21)

$$CoC_{x,y} = \frac{E[(X-\mu_x)(Y-\mu_y)]}{\sigma_x\sigma_y} \quad (21)$$

where σ_x and σ_y are the standard deviation of a unique and improved image. μ_x and μ_y are the mean of the unique and improved images.

6. Edge Preservation Index (EPI):

Edge Preservation Index (EPI) is the class appraisal limit used to find the proportion of edge protection after de-noising the picture. Especially in clinical picture upgrade, it is important to de-commotion the picture just as save the edges to forestall the loss of information. EPI can be mathematically communicated with X is the real image and Y is the reinstated image, M & N shows the count of rows and columns respectively from the input image as followed as (22).

$$EPI = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N-1}|Y(m,n+1)-Y(m,n)|}{\sum_{m=1}^{M}\sum_{n=1}^{N-1}|X(m,n+1)-X(m,n)|} \quad (22)$$

***7.** Iris Datasets of Diabetic Retinopathy*

The dataset used to study the evolution of performance is detailed in table 3. Following basic noise removal algorithms are evaluated on the diabetic retinopathy dataset into account.

i. Median Filter
ii. Average Filter
iii. Weiner Filter
iv. Noise Removal by FFT and IFFT

PSNR, Correlation of Coefficient, and RMSE are the parametric tools used for the estimation of the dataset provided.

Table 3: Database and Count of Images for the Analysis

Dataset	Count of Images (Normal)	DR Images	Count in Total
DIARETDB0	55	61	116
HRF	15	15	134
DRIMDB	55	125	180

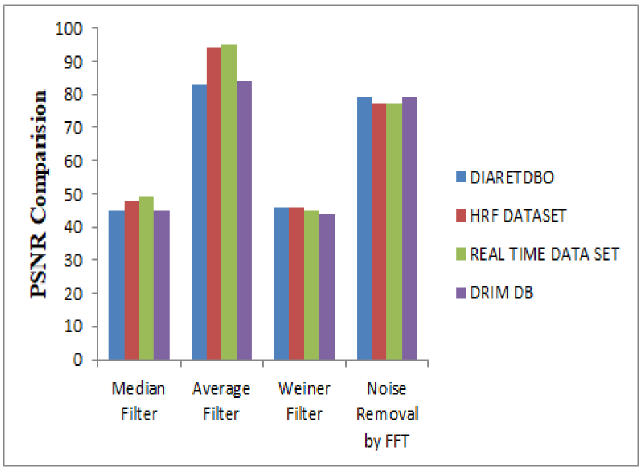

Figure 9. Comparison of PSNR values.

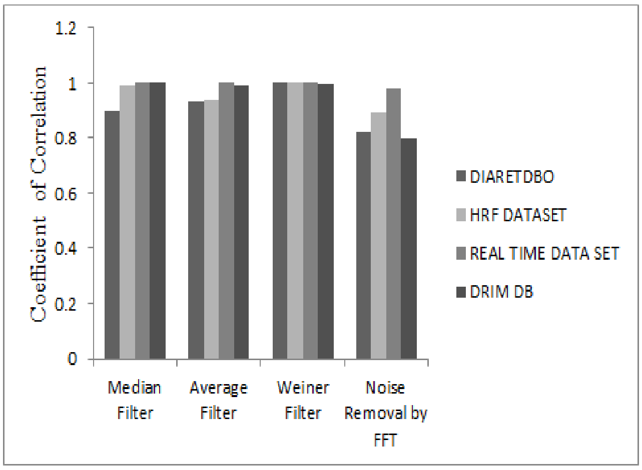

Figure 10. Comparison of Coefficient of Correlation

The higher value of PSNR for all diabetic retinopathy datasets under consideration, figure 9 proves average filter to be the best amongst all noise removal techniques under consideration. Figure 10 and figure 11 shows the comparison of Correlation of Coefficient and RMS values respectively for all the diabetic retinopathy datasets under consideration.

V. CONCLUSION AND FUTURE SCOPE

In this paper, a relative examination of different and efficient approaches adopted aimed at image denoising, contrast enhancement, vessel segmentation, vessel enhancement along with the comparison of different filters has been done. This paper also set flame for a comparison of linear and non-linear methods. Here, also made a comparative study on different scaling techniques used for performance evaluations in the area of image processing. Finally, it is concluded with a detailed review of different literature regarding the methods, datasets, their evaluation, and some key advantages used for the analysis of DR in the Pre-processing of different images.

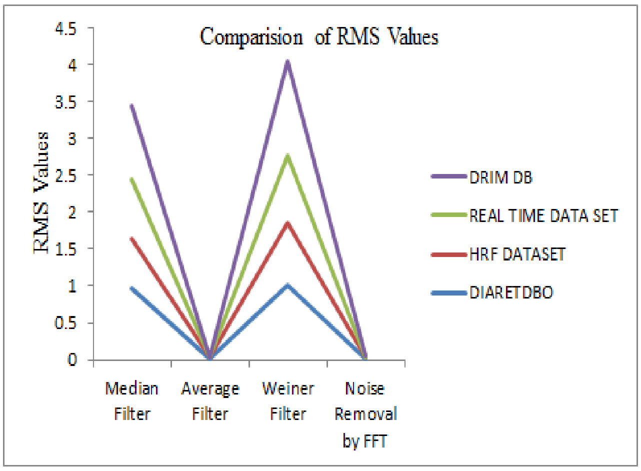

Figure 11. Comparison of RMS values of Datasets.

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AUTHORS PROFILE

Mrs. Bindhya P.S, received the B.E and M.E degree in Computer Science and Engineering from Anna University.Currently, she is pursuing Ph.D. in the same fieldfrom Noorul Islam Center for Higher Education, India. Currently she is working as Assistant Professor Department of Computer Science and Engineering, John Cox Memorial CSI Institute of Technology,Thiruvananthapuram, Kerala and has 9 years of experience in teaching.Her research area includes Biomedical Image Processing, Signal Conditioning and Deep Learning.

Dr.R.CHITRA is currently working as Associate Professor of Computer Science and Engineering at Noorul Islam Centre for Higher Education and has 18 years of experience in the field of Computer Science and Engineering. She received B.E degree in Electrical and Electronics Engineering and M.E degree in Computer Science and Engineering , PhD degree in Computer Science and Engineering from ManonmaniamSundaranar University. She has published 14 papers in the field of Data mining, Artificial Intelligence and Soft Computing. Her research area of include data mining, intelligent technique and bioinformatics.

Prof. V.S. Bibin Raj, is currently working as Associate Professor & Head, Department of Electrical and Eelctronics Engineering, Heera College of Engineering and Technology, Thiruvananthapuram, Kerala with an experience of 14 years in the same field. He received the B.Tech in Electrical and Electronics Engineering and M.Tech in Applied Electronics, Anna University and pursuing Ph.D. in Electrical and Electronics Engineering from Noorul Islam University, India. He has published 8 papers in the field of Power Electronics, Renewable Resources, and Image Processing.