De-noising and contrast enhancement of fundus image through integration of filtering techniques with CLAHE

Report submitted in partial fulfillment of the requirement for the degree of

Master of Technology

in

Computer Science & Engineering

Under the Supervision of

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&
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By

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DECLARATION BY THE SCHOLAR

I hereby declare that the work reported in this dissertation entitled "**De-noising and contrast enhancement of fundus image through integration of filtering techniques with CLAHE**" in partial fulfilment of the requirements for the award of the degree of **Masters of Technology** in **Computer Science and Engineering** submitted at Jaypee University of Information Technology, Solan (India) under department of Computer Science & Engineering and Information Technology, is an authentic report of my work carried out under the supervision of **Dr. S.P. Ghrera and Dr. Amit Kumar Singh**. I have not submitted this work elsewhere for any other degree or diploma.

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CERTIFICATE

This is to certify that thesis report entitled **"De-noising and contrast enhancement of fundus image through integration of filtering techniques with CLAHE"**, submitted by Sonali in partial fulfillment for the award of degree of Master of Technology in Computer Science & Engineering to Jaypee University of Information Technology, Waknaghat, Solan has been made under my supervision.

This report has not been submitted partially or fully to any other University or Institute for the award of this or any other degree or diploma.

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ABSTRACT

Now-a-days medical fundus images are generally used in clinical diagnosis for the recognition of retinal disorders. Fundus images are generally degraded by noise and also suffers from low contrast issue. These problems make it difficult for ophthalmologist to detect and interpret diseases in fundus images. This thesis work presents a noise removal and contrast enhancement algorithm for fundus image enhancement by combining filters with Contrast Limited Adaptive Histogram Equalization (CLAHE) technique. Primarily input fundus image is divided in to red, green and blue components. Further filtering process is applied on each component respectively to remove noisy pixels and finally CLAHE technique is applied to increase contrast of the de-noised fundus image. The efficacy of the proposed method is claculated through different performance parameters like Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Correlation coefficient (CoC) and the results indicate that the proposed algorithm is better than simple CLAHE technique.

In this thesis work, Chapters are prearranged as follows.

CHAPTER 1 gives the introduction about the medical image enhancement, its background, techniques and basic concepts about the fundus image and its enhancement.

CHAPTER 2 highlights the related work done in the field of the medical image enhancement and focus on fundus image enhancement and its related work to it.

CHAPTER 3 explains the proposed algorithm, methodology used and also gives the simulation results and analysis of the proposed algorithm.

CHAPTER 4 gives a brief description about the tools used for simulation and also databases used for the proposed algorithm simulation.

CHAPTER 5 concludes the overall work done in this thesis and also gives the future scope of the work done.

CHAPTER 1

MEDICAL IMAGE ENHANCEMENT: AN INTRODUCTION

1.1 Basic Concepts of Medical Image Enhancement

During communication the data parameters of digital images suffers from different types of noise [1]. Imperfect gadgets and atmospheric turbulence are the main cause of the generation of noise and this conveys wrong information about the image. Other sources of noise are noisy channel, faulty pixels in camera sensors and faulty memory location. The noise degrades the quality of image and important information's are lost [25]. Digital image processing is the processing of digital images for storage, transmission and representation of image for human interpretation and for machine perception. The area of digital image processing has developed vastly and plays a significant character in processing of digital medical imaging modalities for diagnose of disease. Recently digital image processing gains a vast area of applications. One of the most important applications is in medical science. A lot of study has been occurred to enrich the image quality and remove noise. Recently, medical image processing and their enhancement is the most significant trend in modern medicine [2].Further, a current 3-D medical imaging technique offer advances in science and as a result higher dependability medical images are created. Different kinds of noise like Gaussian, impulse, Poisson, Rician and Speckle noise corrupt the medical images [38, 45]. Medical images likely X-ray, Magnetic Resonance Imaging (MRI), Computed Tomography (CT), ultrasound, Optical Coherence Tomography (OCT), Single-Photon Emission Computed Tomography (SPECT), Heidelberg Retina Tomography (HRT) and fundus are usually have very low contrast and the work of image enhancement algorithms is to sharpen them. Figure 1.1 shows the effect of medical image enhancement.

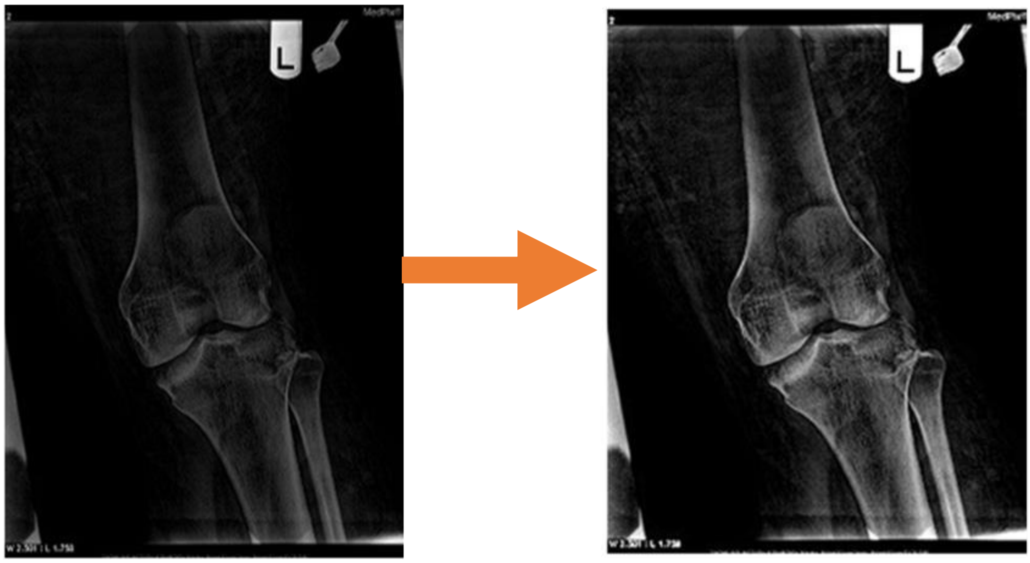


Fig 1.1.Showing effect of medical image enhancement on MRI image of a left knee

1.2 MEDICAL IMAGE PROCESSING

Medical image processing is the processing of medical images whose inputs and outputs are images that extract essential data and features from medical images. Figure 1.2 shows the basic building blocks of medical image processing. The fundamental steps vary from type to type of medical image modality. Some of the basic steps in medical image processing are briefly explained below.

1.2.1 Image acquisition

Acquisition is the primary step in medical image processing. In this step the image is retrieved from the source for further processing.

1.2.2 Preprocessing

After acquiring the image, preprocessing is done at the basic level of abstraction of image and it envelops various further steps to enhance medical image or to remove noise or distortion from medical image for further processing of image. Some of the preprocessing steps are explained below.

- **Image enhancement**

  This step is an important and most challenging area in medical image processing. The main aim of this step is, to suppress the noise while preserving the edge details [25].Medical image enhancement techniques enhances the perception and interpretability of data present in the image [38].

- **De-noising**

  It is one of the crucial step in preprocessing of medical image. Noise occurs in an image during acquisition or communication. Main motive of de-noising is to preserve edges while removing the noise from medical image. Different types of filters are used to remove the noise.

- **Contrast Enhancement**

  This step converts low contrast image to high contrast image. It aims at improvising the visual quality of medical image. It improves the brightness of image between its objects and background [37].

- **Image Edge Enhancement**

  It is one of the main steps for improvising the quality of medical image. Guided Filter technique is used to enhance the medical image edges [43].

1.2.3 Segmentation

The next step after preprocessing is Segmentation of image, means to split or divide image into multiple sub-parts so that it become more easier to extract relevant information and identify objects under consideration from image.

1.2.4 Feature extraction

This process is performed to change the segments of the image into more convenient form that better describes the main features and attributes of interest of image.

1.2.5 Classification

Then classification is performed on the pixels of the medical image to divide pixels among the classes or categories of interest. A function is used to assign pixels of image to its respective class or domain.

1.2.6 Post-processing

The final step is post-processing, which removes the blocking artifacts occurred due to transformation method (orthogonal) applied to image, decompress the compressed image and to recognize objects in the image.

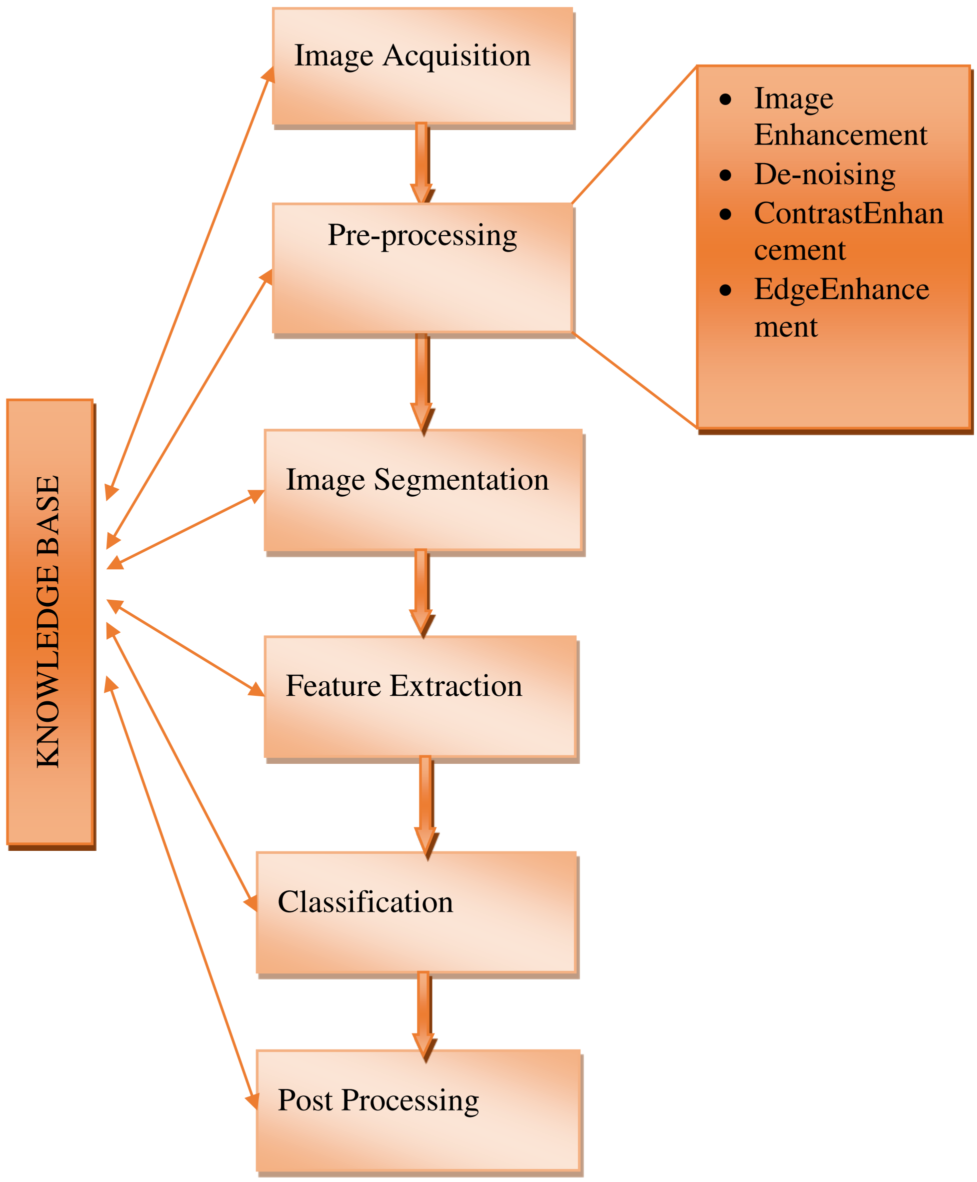


Fig 1.2. Building blocks of medical image processing

1.3 Medical Image Modalities

On the basis of the how medical image is produced and looks, digital medical images are categorized into many types. Some common types of medical images are:

1.3.1 X-Ray

X-rays are radiations just like visible light, radio waves and microwaves. It possesses very high energy level. X-ray is allowed to enter into patient's body to image the area of interest. The images by x-ray show the parts of body in different shades because of the reason that distinct tissues in human body absorb different scale of energy's radiations. For e.g. Calcium in human bones absorbs x-rays in the largest amount, as a result bones look white after imaging [44].

1.3.2 Computerized Tomography (CT)

It is also termed as Computerized Axial Tomography (CAT). X-rays are used in this imaging technique to create detailed cross-sectional images of internal area of human body like blood vessels, bones and organs.

1.3.3 Magnetic resonance imaging (MRI)

Strong magnets and radiofrequency pulses are used by this imaging technology to create images. These signals are detected by a radio antenna is used to detect the signals. This imaging method can acquire 3 dimensional images. MRI has gained a large popularity among the modality. MRI is used to take the image of breast tissue, brain, spinal cord, heart, bones, joints, blood vessels, and other internal organs.

1.3.4 Ultrasound

High-frequency sound waves are used to capture ultrasound images. It is vastly used due to its simplicity and less expensive. A transducer is used to send and receive the signal. The transducer transmits the high-frequency sound waves into human body, those waves are then returned back accordingly to the tissues in the body to which they strike in different manners. Then the reflected sound waves are transformed in the form of electric signals and hence as a result moving image shows on the display screen.

1.3.5 Optical Coherence Tomography (OCT)

OCT is the latest technology in the field of medical imaging. Like Ultrasound, it also uses light waves to scan body parts and take cross-sectional higher resolution images. It is basically used to examine parts of eye (specifically retina).

1.3.6 Single photon emission computed tomography (SPECT)

A new technology for medical imaging that is used for special form of scan that use radio-active material and a specific purpose camera that take 3-dimensional images of body. SPECT imaging have specialty that it can show the actual working of human body organs. For e.g. SPECT is able to show how blood flows to human heart.

Table 1.1 illustrates the comparison of multiple medical image modalities based on resolution, speed of acquisition, cost, rate of data acquisition, effects to human body and their availability. Figure 1.3 shows different image modalities.

Table 1.1. Comparison of various medical images

Modality / Properties	**X-Ray**	**CT-Scan**	**MRI**	**Ultrasound**	**OCT**	**SPECT**
Image Resolution	Normal	Moderate	High	Depends upon transducer selection	Better than MRI and Ultrasound	High
Time required for acquisition	Less	Moderate	Long	Depends on operator	Less	Moderate
Cost	Low	Costlier	Costlier	Moderate	Costlier	Costlier
Data Acquisition	Less	Improved	Improved	Less	Improved	Improved
Effects on human body	Harmful to human body due to ionization effect	Harmful to human body due to ionization effect	No effect	Harmful to human body due to non-ionization radiation effect	No effect	Harmful to human body due to ionization effect
Implementation	High	High	Less than CT	High	Moderate	Moderate

1.4 Noise in Medical Images

Noise may be introduced in medical images during the acquisition or transmission processes. Different categories of noises such as Gaussian, Impulse, Poisson and speckle noise degrades medical images. Figure 1.4 shows the degradation and reconstruction model of medical images. Nature of noise in medical image may be additive noise or multiplicative noise depends on the image accusation system. Example of additive noise is Gaussian noise, mostly available in all kind of medical images. It is uniformly added with the pixel intensity, in the medical image. Speckle noise which affects more to ultrasound image and OCT image, is a multiplicative noise. Multiplicative noise is multiplied with the pixel intensity, in the medical image. Different medical image noise and their characteristics are discussed in table 1.2 below. Figure 1.5 shows the effect of noise in medical image.

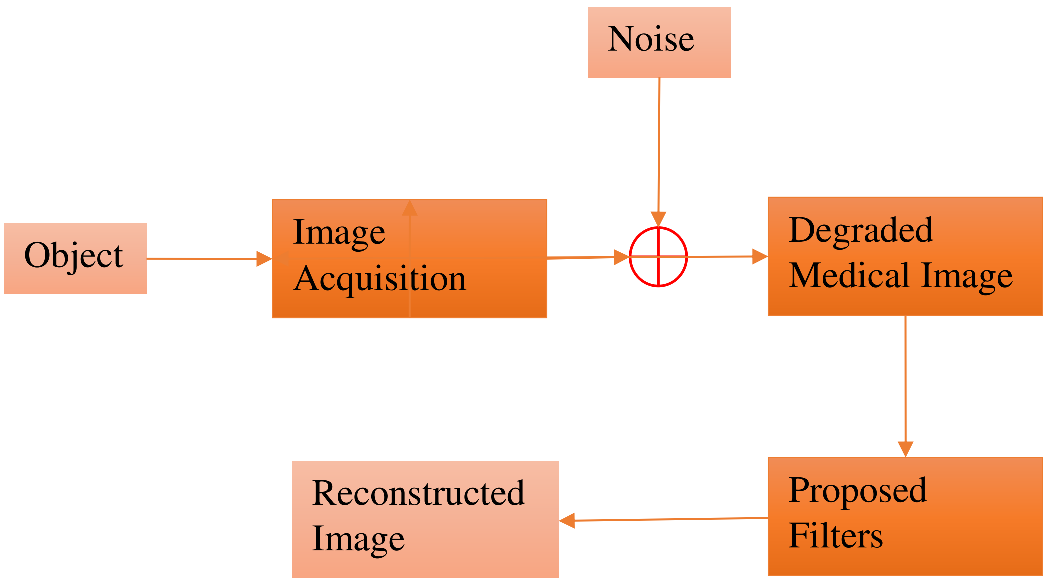


Figure 1.4: Image degradation and reconstruction model

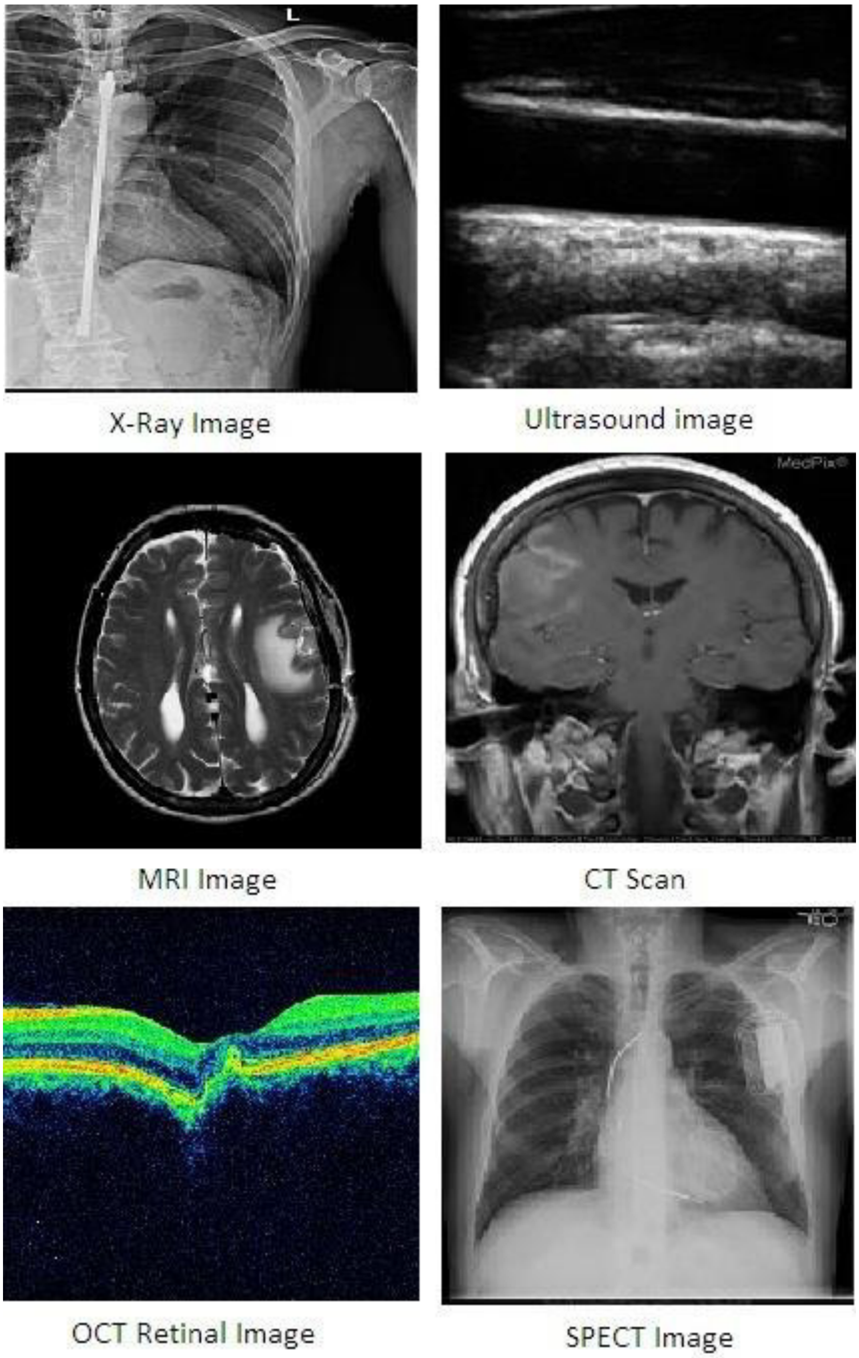


Figure 1.3: Important image modalities

Table 1.2. Showing some popular noises found in medical images

Noise type	Description
Gaussian Noise (Amplifier noise)	• Thermal vibration of atoms, amplifier noise and radiation of warm objects are the main cause of the generation of this noise. • Also acknowledged as white noise or amplifier noise. • Tends to change the pixel values in digital images. • Gaussian noise spreads evenly on the image and has Gaussian distribution in structure. • This noise is found in MRI image. • The probability distribution function is of bell shape [1] and is expressed by $$W(f) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(f-n)^2}{\sigma^2}}$$ Here f= gray level n =mean value of Probability density function σ = noise standard deviation
Salt and Pepper Noise (Impulsive noise)	• Most commonly acquired in acquisition of image, transaction, storage and processing of images. • Impulse noise degrades the quality of image as well aslost the information details. • Also known as intensity spikes, this noise is of impulse type and is caused by error in transmission of data. • This noise is found in fundus image. • The following expression shows the distribution of impulse noise $$f(\mathrm{N}) = \begin{cases} \mathrm{p_a} & \text{for N} = \mathrm{a} \\ \mathrm{p_b} & \text{for N} = \mathrm{b} \\ 0 & \text{otherwise} \end{cases}$$ Where $a, b \in \mathcal{R}$

	p_a=Probability of a p_b= Probability of b N= Random Variable
Speckle Noise	• Speckle noise is multiplicative in nature, so multiplied with the image pixel values. • Medical images such as ultrasound image and OCT image are suffered from speckle noise. • The degraded image resulting from speckle noise is expressed as $$G(n,m) = X(n,m) * S(n,m) + \eta(n,m)$$ Where $G(n,m)$=Observed image with pixel values (n,m) $X(n,m)$=Original image $S(n,m)$= Speckle noise $\eta(n,m)$ =additive noise
Poisson noise (Photon noise)	• X-rays, visible lights and gamma rays are the causes of the generation of Poisson noise. • These sources are having random fluctuation of photons. Result gathered image has spatial and temporal randomness. This noise is also called as quantum (photon) noise or shot noise [46]. • This noise caused due to the insufficient capture of photons, which do not provide sufficient statistical information. • The distribution of poisson noise is given by $$P(k) = \frac{(\lambda^k e^{-\lambda})}{k!}$$ Where λ= Number of events occurred during the considered time interval, e= Euler's number,

	k= is the event index or number.

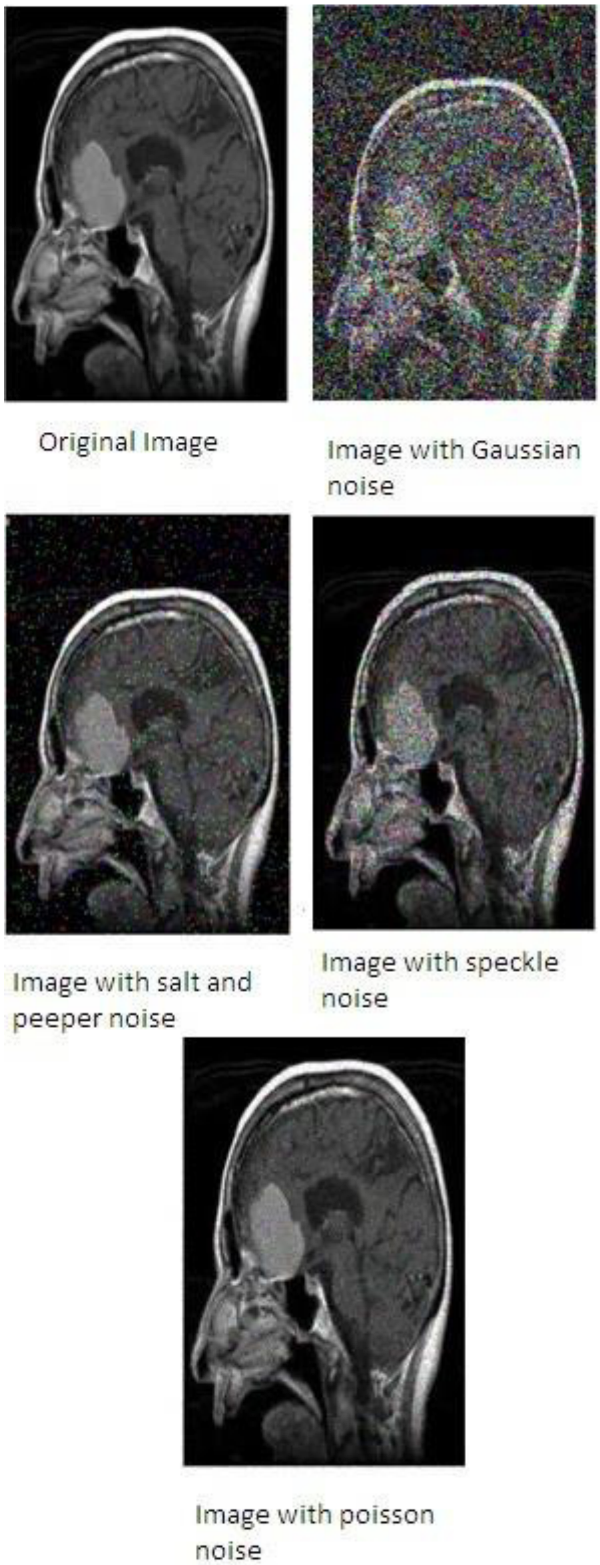


Figure 1.5: Effect of noise in medical image

1.5 Performance Metrics

Performance metrics are used to evaluate efficiency of different of image enhancement techniques. Some of the most commonly used performance metrics are described in Table 1.3 and Table 1.4 shows the image quality parameters used to evaluate the performance by comparing the input pixels with the corresponding output pixels.

Table 1.3: Different performance metrics to evaluate enhancement techniques

Metric	Characteristics
Mean square error (MSE)	• This metric shows the difference of original image and recovered image. • A low value of MSE indicates high performance. • MSE can be defined by the following expression $$\text{MSE} = \frac{1}{m \times n} \sum_{i=1}^{m\times n} (\hat{y}(i,j) - y(i,j))^2$$ Where $m \times n$ is the size of image $\hat{y}(i,j)$=Recovered image $y(i,j)$=Original image
Peak Signal to Noise Ratio (PSNR)	• PSNR can be expressed as $$PSNR = 20 \log_{10} \frac{255}{\sqrt{mse}}$$ • High value of PSNR is required for high performance
Root Mean Square Error (RMSE)	• RMSE can be expressed as RMSE=$\sqrt{\frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n}(\hat{y}(i,j) - y(i,j))^2}$ • Less value is required for high performance.
Mean Absolute Error (MAE)	• MAE can be expressed as

	MAE=$\frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\lvert\hat{y}(i,j)-y(i,j)\rvert$ • A small value is required for good performance

Table 1.4: Different Image Quality parameters

Metric	Characteristics
Structural Similarity Index (SSIM)	SSIM can be expressed as: $\mathrm{SSIM(X,Y)} = \left[l(\mathrm{X,Y})^{\alpha}.\,\mathrm{c(X,Y)}^{\beta}.\,\mathrm{s(X,Y)}^{\gamma}\right]$ Where 'X, Y' are two windows of same dimension of original and reconstructed image respectively. α,β,γ are the weights assigned to these parameters. *l*, c and s are the luminance, contrast and structure respectively, which together combine with certain weights to form SSIM and are computed as $$l(X,Y) = \frac{2\mu_X\mu_Y + c_1}{\mu_X^2 + \mu_Y^2 + c_1}$$ $$c(X,Y) = \frac{2\sigma_X\sigma_Y + c_2}{\sigma_X^2 + \sigma_Y^2 + c_2}$$ $$s(X,Y) = \frac{\sigma_{XY} + c_3}{\sigma_X\sigma_Y + c_3}$$ Here 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*, σ_{XY} is the co-variance of *X* and *Y*, c_1 and c_2 are the two parameters to stable the division with poor denominator, $c_3 = \frac{c_2}{2}$, When value of SSIM approaches to 1 shows better similarity between original image and recovered image.

Edge preserving Index (EPI)	EPI can be expressed as: $EPI = \frac{\left(\sum_{m=1}^{M}\sum_{n=1}^{N-1}\lvert X'(m,n+1)-X'(m,n)\rvert\right)}{\left(\sum_{p=1}^{M}\sum_{q=1}^{N-1}\lvert X(m,n+1)-X(m,n)\rvert\right)}$ Where X' is the reconstructed image, While 'X' is the original image, 'M' is the rows count in image, 'N' is the column count in image. When value of EPI approaches to 1 shows better preservation of edges in the image.
Correlation Coefficient (CoC)	CoC can be expressed as: $CoC_{X,X'} = \frac{(E[(X-\rho_X).(X'-\rho_{X'})])}{\sigma_x\sigma_{X'}}$ Where $\rho_X$and $\rho_{X'}$ are the average of the original and recovered images, $\sigma_x$and$\sigma_{X'}$are standard deviation of original and recovered image. When value of CoC approaches to 1 shows the better co-relation between images under consideration.

1.6 MEDICAL IMAGE ENHANCEMENT TECHNIQUES

Figure 1.6 shows the major classification of medical image enhancement techniques. The enhancement techniques can be classified into two main domains: 1) Spatial Domain, and 2) Transform Domain

1.6.1 IMAGE ENHANCEMENT IN SPATIAL DOMAIN

In this type of enhancement technique, the process is based on direct manipulation of pixels in an image. Spatial domain techniques can be expressed as:

$$O(x,y) = T[I(x,y)] \tag{1}$$

Where, $I(x,y)$= input image, $O(x,y)$ = processed image, T = Transformation operator on 'I', defined over some neighborhood of (x,y).

Bhattacharya et al. [30] developed a single value decomposition (SVD) to enhance the contrast of an image. This technique worked on enhancement of visual information of an image using multiple steps such as contrast enhancement, de-blurring and de-noising.Yiwen Dou et al. [6] presented an image enhancement method based on hue and Chroma constraint to extract visual attention focus in accuracy. In this method, initially the RGB color space should be translated to YCbCr, after that the iteration image enhancement model was applied in constraint of Chroma and hue. Then the remaining image evaluation function implements closed-up control to adjust the iteration step and enhancement performance. Some of the popular spatial domain enhancement techniques are explained below.

1.6.1.1 Gray Level Transformation

One of the basic spatial domain image enhancement techniques is gray level transformation. Pixels value before and after processing, are correlated by an equation in the form

$$s = T(r) \tag{2}$$

Here 'T'is a transformation function which corresponds a pixel value in original image 'r'into a pixel value in processed image 's'.

1.6.1.2 Image Negative

The image negative is obtained by the negative transformation given by the following equation.

$$O = M - 1 - I \tag{3}$$

I= input image

O= output image

The gray level ranges from0 to $[M - 1]$

Equation (3) reverses the values of intensity levels of an image and gives an equivalent of negative image. This enhancement technique enhances white or gray pixels encapsulated in dark regions, particularly when black areas are principal one [25].

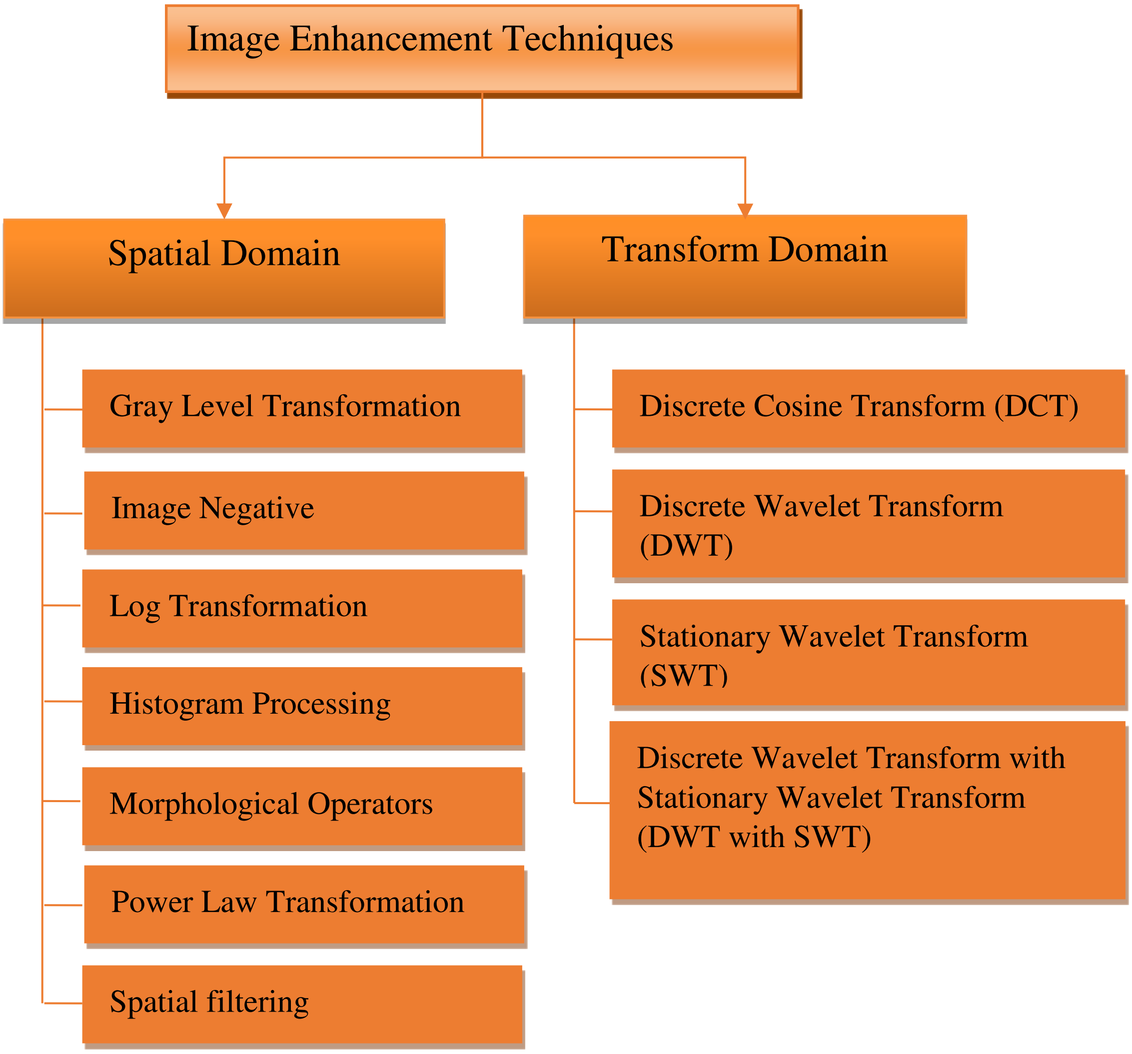


Fig.1.6 Classification of medical image enhancement techniques

1.6.1.3 Log Transformation

The log transformation technique limits the range of images with changes in intensity values [16]. It is formulated as

$$O = c * \log(1 + I) \tag{4}$$

Here 'c' is a constant, 'I' is input pixel value and 'O' is output pixel value.

This transformation widens the dark pixel values in an image while low gray-level values into a broad range and vice-a-versa for higher values [25].

1.6.1.4 Histogram Processing

Histogram processing technique regulates the image intensities to enhance the contrast of the digital image. Histogram is used to represent frequency of appearance of all the levels in the image [37]. Khan et al. [8] used histogram equalization technique to enhancement the image contrast. Let 'I' be an image described as a matrix of integer pixels varying from 0 to M-1. Here, 'M' is total number of possible intensity values, mostly 256. Let 'O' designate the normalized histogram of 'I'.

$$O_n(\text{normalized histogram}) = \frac{\text{number of pixels with intensity (n)}}{\text{total number of pixels}} \quad (5)$$

Histogram Equalization (HE) is denoted by 'g' and is formulated as

$$g_{i,j} = \left\lfloor (M-1) \sum_{n=0}^{f_{i,j}} (O_n) \right\rfloor \quad (6)$$

Here, '$g_{i,j}$is the equalized histogram, 'O_n' is the normalized histogram and 'M' is the interval value i.e. [0, M-1].

Liang hua et al. [32] proposed an enhancement method for color medical image. This technique used histogram equalization to obtain enhanced intensity numbers matrix**.**

1.6.1.5 Morphological Operators:

Morphological Operators are based on the mathematical axioms and relationships between classes to extract the important information of an image. Morphological operators are of basically two types:

a) **Top-Hat Transformatio**n: It operates like a high-pass filter and extracts the small details from an image. It is found by subtracting the original image opening 'I' by some structural element 'b' from image itself. Top-Hat Transformation is defined as

$$T_{th}(I) = I - I \circ b \quad (7)$$

Here 'T_{th}' is the image after top-hat transformation, 'I∘ b' is the opening of image 'I' by structural element 'b'.

b) **Bottom-Hat Transformation**: It is used for dark objects on light background and is found by subtracting the original image from its closing.

$$T_{bh}(I) = I - I \cdot b \quad (8)$$

Here 'T_{bh}' is the image after bottom-hat transformation

'I· b' is the closing of image 'I' by structural element 'b'.

Rajendran et al. in [43] combines the morphological transformation technique with edge filter to solve the issue of the edge degradation in medical images. This methodology put into use the combination of guided filter with edge enhancement and contrast stretching and hence the results obtained were lesser noise in CT images as well as X-ray images as compared to some other enhancement methods. Kurt et al. [36] proposed an enhancement technique of medical images which based on Top-Hat morphological transform, Contrast Limited Histogram Equalization (CLAHE) and anisotropic filter to improve the contrast and also to enhance the quality of specific visual areas that are of particular interest. When Enhancement measure (EME) of original image and enhanced image was compared, this method gives very beneficial results.

1.6.1.6 Power Law Transformation

It is a category of gray level transformation. Mathematically it is written as

$$O = cI^{\gamma} \tag{9}$$

Here 'c' and 'γ' are constant, 'I' is normalized input pixel values and 'O' is normalized output pixel values. Power law transform removes the drawbacks of Log transform with the help of different 'γ' values.

1.6.1.7 Spatial Filtering

Filtering in the spatial domain enhancement method involves the determination of the processed value of the prevailing pixel based on the value of the neighboring pixels [1]. Mean filtering and median filter are of this type. There filters are broadly classified as linear and non-linear filters based on the method how current and neighbor pixels are correlated.

Gerig et al. [47] presented a spatial filtering technique (i.e. post-processing technique) for de-noising and boundary enhancement of medical image (Medical Resonance Imaging (MRI)) based on the technique of "Nonlinear Anisotropic Filtering". Output of this technique comes out to be quite impressive as it satisfies all the parameters for which it was developed i.e. the output filtered image was quite clear than before and also image boundaries was more precise than before.

1.6.2 IMAGE ENHANCEMENT IN TRANSFORM DOMAIN

This processing technique are based on transforming the image from one form to another form by applying some filter function to the image and return to the original form that results enhanced image [17]. Different transform functions such as discrete cosine transform (DCT), Fourier transform, discrete wavelet transform (DWT) and Stationary Wavelet Transform (SWT) are used to enhance the image [13-19]. The transform coefficients are manipulated to improve the quality of an image. The block diagram of transform domain image enhancement technique is shown in figure 1.7.

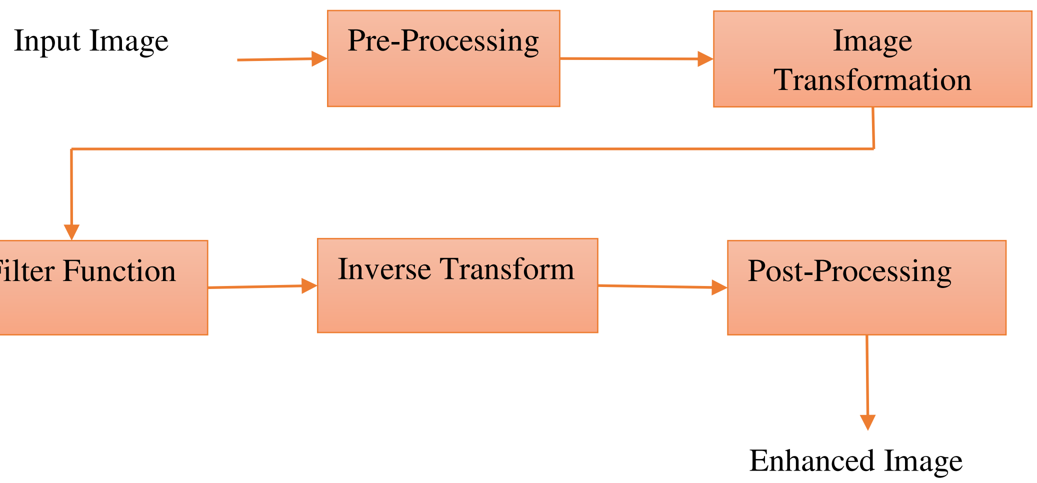


Fig. 1.7 Block diagram of transform domain image enhancement technique

Qin Xue in 2013 [31] proposed a new methodology for medical image enhancement by imposing local range modification in shearlet domain using "Shearlet Transformation". Some of popular enhancement techniques in transform domain approach are discussed below.

1.6.2.1 Discrete Cosine Transform (DCT)

This method enhances image resolution by image stretching with minor or slight loss. In DCT most of the power is concentrated in lower frequency bands and also DCT have efficient energy compaction property. These properties of DCT help in Human Visual System (HVS) as HVS is higher sensitive to chrominance than luminance. Poor contrast is the main limitation of DCT [42].Figure 1.8 shows the block diagram of DCT based image enhancement technique. In this figure input image is subjected to DCT and then filter function is applied on it. Inverse DCT (IDCT) is then applied to get back the output image.

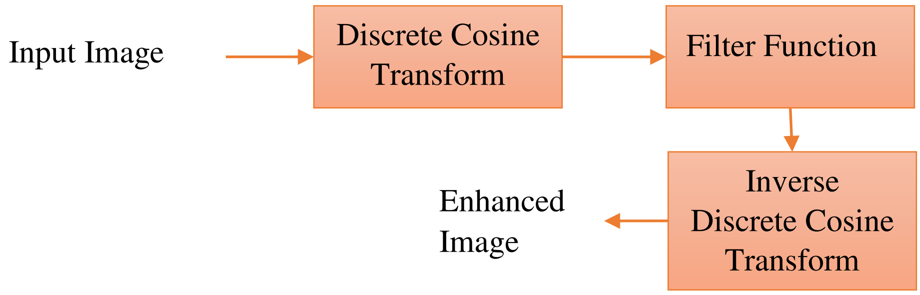


Fig.1.8. Block diagram of DCT based image enhancement technique

1.6.2.2 Discrete Wavelet Transform (DWT)

DWT basically conserves the high frequency components. Firstly the input image is classified into four sub-bands by applying the DWT to image. The four sub-bands are, low-low (LL), high-low (HL), low-high (LH), and high-high (HH).For a two-level DWT, the LL sub-band is further divided into four sub-bands (LL_1, HL_1, LH_1 and HH_1). For next higher levels the above mentioned procedure continues recursively. Figure 1.9 shows the sub-band decomposition of a two-level DWT. Then thresholding is further applied to the sub-band coefficients to enhance the wavelet coefficients. Two major categories of thresholding are there. They are soft thresholding and hard thresholding.

Hard and soft thresholding functions are formally expressed as:

$$\text{Hard thresholding: } H_{th}(x) = \begin{cases} x & if x \geq Th \\ 0 & Otherwise \end{cases} \tag{10}$$

$$\text{Soft thresholding: } S_{th}(x) = \begin{cases} x - Th & if x \geq Th \\ 0 & if x < Th \\ x + Th & if\ x \leq -Th \end{cases} \tag{11}$$

Where, 'Th' is the given threshold level parameter for wavelet coefficients. Hard thresholding basically keeps the coefficients above the threshold while attenuates the coefficients below that threshold level whereas soft thresholding narrows the coefficients above the threshold level. The continuity feature of soft thresholding is quite advantageous over the features of hard thresholding. Figure 1.10, 1.11 and 1.12

show the original signal, hard thresholding signal and soft thresholding signals respectively. After shrinkage of wavelet coefficients inverse DWT (IDWT) is applied to recover the enhanced image [20-22]. DWT gives more sharp images with edge information but losses content at higher frequencies [42]. Figure 1.13 shows the block diagram of DWT based image enhancement technique.

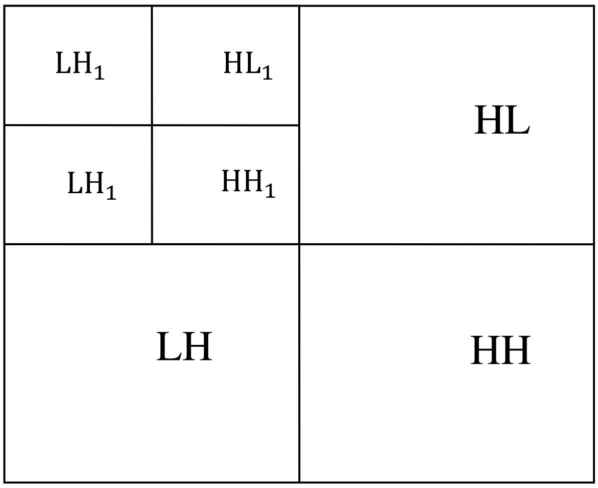


Figure 1.9 Sub-band decomposition of two-level DWT

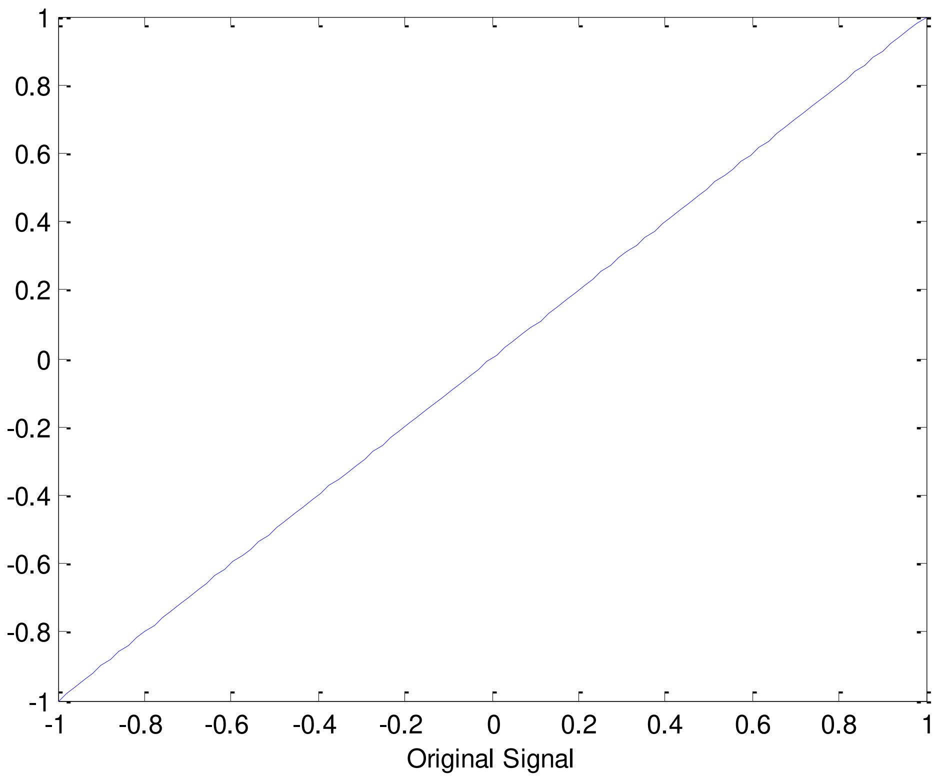


Figure 1.10: Original signal

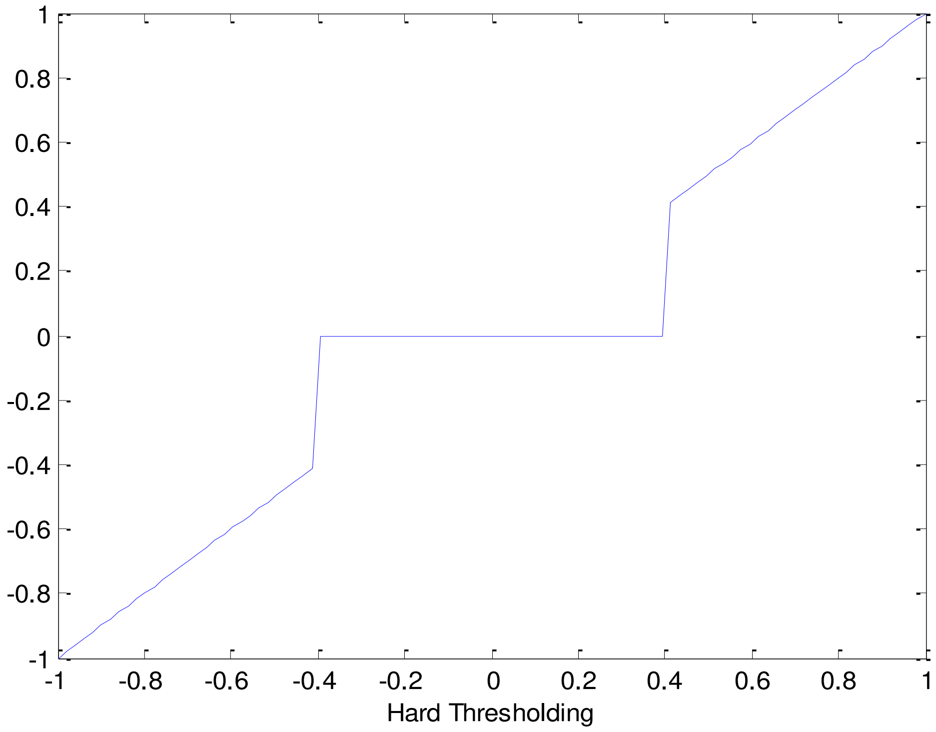


Figure 1.11: Hard Thresholding of the original signal with threshold valueTh =0.4

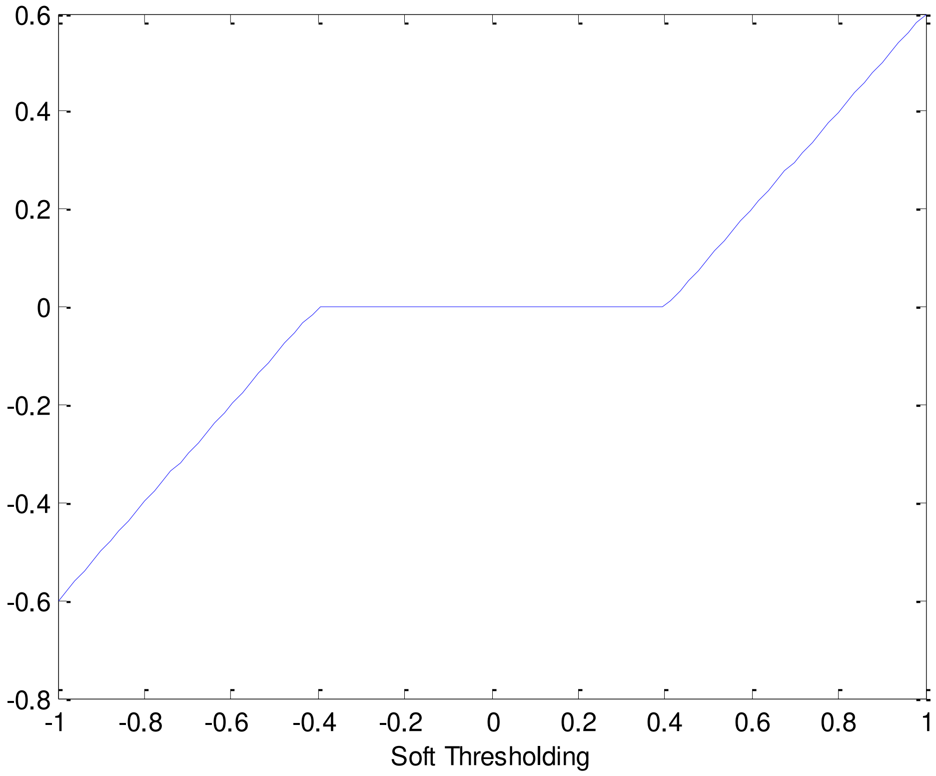


Figure 1.12: Soft Thresholding of the original signal with threshold value Th=0.4

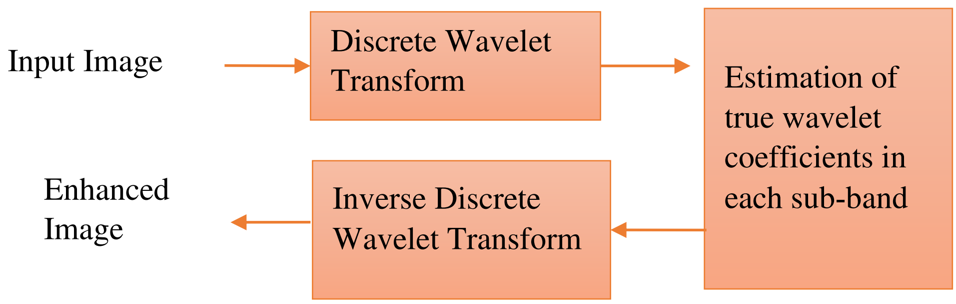


Fig.1.13 Block diagram showing DWT based image enhancement technique

1.6.2.3 Stationary Wavelet Transform (SWT)

In this technique, the input image is converted to coefficients by taking the SWT. The LH, HL and HH sub-band coefficients are manipulated to get the enhanced image. Bi-cubic interpolation is done for enhancing image resolution as it gives smooth edges with less blurring. High frequency components are conserved by this technique. Compared to DWT SWT has more complexity [42]. Figure 1.14 shows the block diagram of SWT based enhancement method.

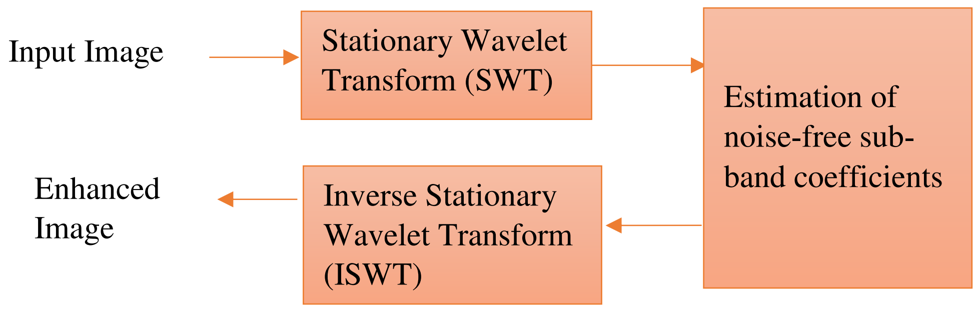


Fig. 1.14 Block diagram of SWT based enhancement method

1.6.2.4 Discrete Wavelet Transform with Stationary Wavelet Transform (DWT with SWT)

In this technique, both the transforms such as DWT and SWT are implemented to divide the image into four sub-bands namely LL, HL, LH, and HH. High frequency components are undergone through Bi cubic interpolation obtained using DWT. Summations of the interpolated sub-bands are made with the sub-bands generated from

SWT. Next the enhanced image is recovered by applying IDWT. The advantage of this technique is that, it prevents the information loss [42]. Figure 1.15 shows the block diagram of the SWT with DWT based image enhancement method.

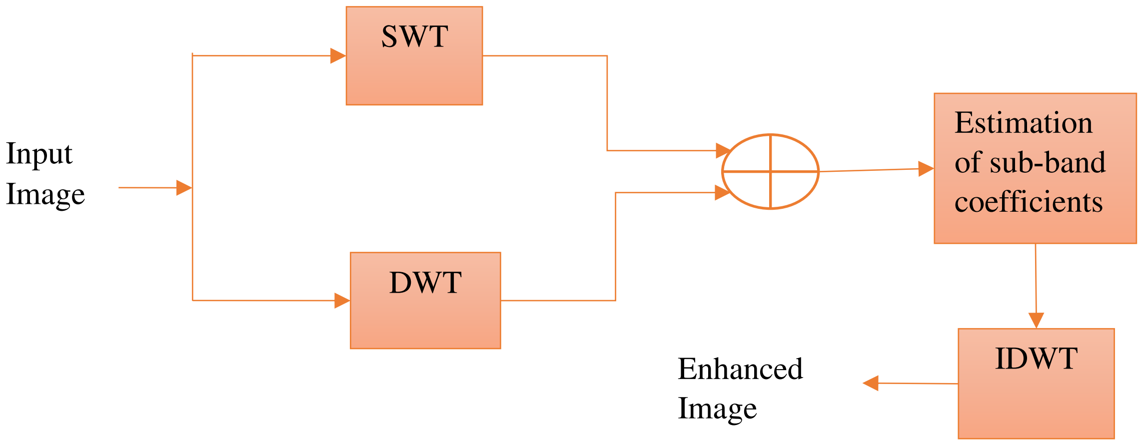


Fig.1.15 Block diagram showing SWT with DWT based image enhancement method

1.7 Basic Concepts of Fundus Image Enhancement

Medical image enhancement for improved diagnosis of diseases is one of the raising field of interest now-a-days among researchers and physicians. Medical image enhancement aims to improve the contrast of medical image and reduction of noise level [48]. One of the featured and important medical image is fundus image. Digital fundus images are taken by fundus camera, retrieving the features like the retina, optic disc area and cup area, macular regions and the posterior surface of an eye. Digital Fundus images are widely used for the detection of the multiple disorders related to eye [50, 52, 53, 55, 56, 57]. Fundus image is caught by the means of standard modality of imaging i.e. Fundus camera,that is traditionally used in hospitals and eye specialist clinics. The medical fundus image presented in figure 1.16, can be quite beneficial in the extraction of many essential features of the retina like Optic Disk Area (ODA), Cup Area, Fovea, exudates and most importantly the blood vessels.

Noise in medical digital fundus image can be acquired because of many stated causes like category of image modality used to acquire fundus image, image acquisition procedure by the means of fundus camera, transmission also lead to noisy pixels to occur in fundus image and uneven illumination is also a key aspect for presence of noisy pixels in the fundus image. Fundus image is mainly affected by two types of noises i.e. Salt and Pepper noise and Gaussian (white) noise [54].

Figure 1.16. Showing retinal fundus RGB image

Preprocessing step in fundus image processing is a crucial step for the detection and removal of noise from digital medical fundus image [48]. Feature extraction from fundus image like fovea, blood vessels, optical disk, etc. [52], normalization of fundus images color and many more for the convenience of the eye-specialists to efficiently detect abnormalities in the eye with the help of it. Fundus image is RGB in nature. Green component of fundus image is the most important as it provides maximum of the feature extraction while blue component is the least important one. Fundus RGB image can be decomposed into different components as shown in figure 1.17 and then essential features can be extracted from them [51], separate pre-processing can be performed on them, and separate de-noising can be performed on these segments. Green channel is one of the most significant channel as most of the important features can be extracted through it [50]. Figure 1.18 demonstrate the diagnostic features that could be mined from individual components of fundus image.

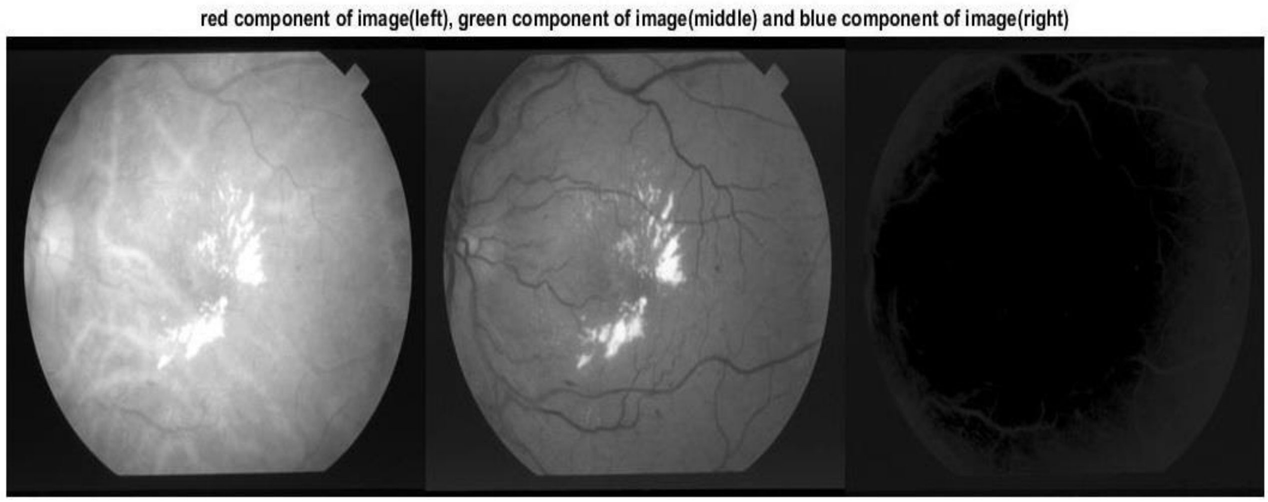


Figure 1.17. Showing red, green and blue components of fundus image

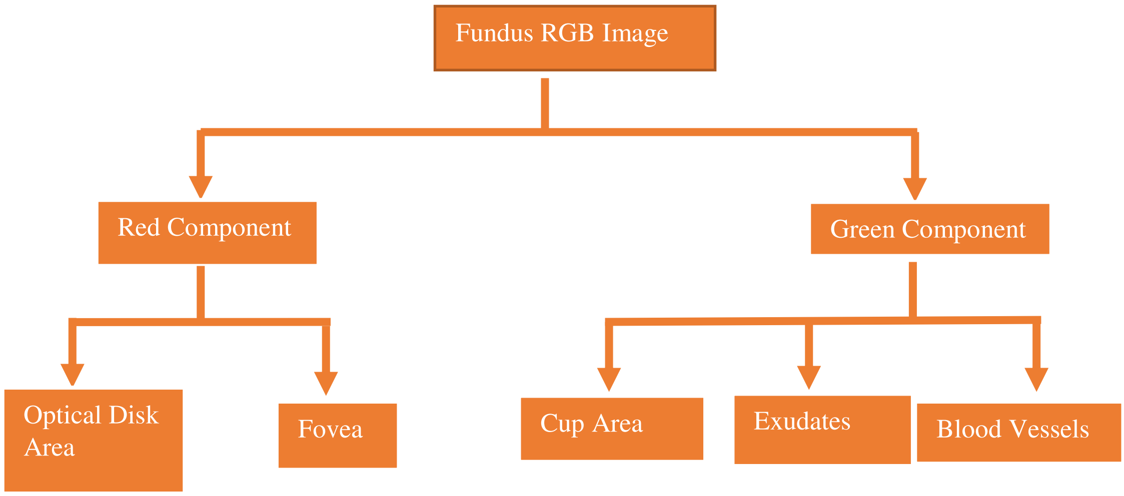


Figure 1.18. Showing different diagnostic features extracted from fundus red and green component

1.7.1 BACKGROUND

De-noising and enhancement of fundus image

Table 1.5 enlightens concisely regarding various filtering techniques employed for removing noise from fundus image. These filters are quite effective in the removal of noises present in fundus image like Gaussian (white noise) and salt and pepper (Impulsive noise), which are detailed in table 1.6.

Table 1.5. Describing various filters used in the de-noising of fundus image

Filter Type	Depiction
Mean Filter or average filter	"It is a spatial filtering technique that replaces the value of pixels in the window with the mean of the pixels value in that window. It is usually used for the purpose of de-noising and smoothening of the image. The noise that mean filter efficiently removes from fundus image is grainy kind of noise.".
Median Filter	It is also a spatial but non-linear filtering technique to remove noise from the image as well as preserve the edge degradation that happens in average filtering. In median filtering, the pixel value that is corrupted is exchanged by the median of that window pixel values. Median filter works well for the fundus image enhancement as compared to other linear filtering methods.
Wiener Filter	A linear filter that is applied often in frequency domain. Weiner filter is best for the removal of additive noise and blur effect in fundus image. It is also acknowledged to be Mean Square Error favorable filter. It works on the noisy signal of the image and toutpus the estimate of the original image.
Gaussian Filter	It is a linear filter that is used to remove noise from the image along with the blurring of image similar to average filter. It differs from average filter in the aspect that it uses different kernel from mean filter which is in the shape of bell curve (Gaussian PDF). In 2-Dimensional, Gaussian has the calculation: $$G'(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$ Here average is (0,0) and σ^2 is the variance (default 1).

Weighted Median Filter	In weighted median filter, the only difference is that mask is not empty by which we multiply the window. In weighted median filter a proper mask is selected with some weights and that is averaged and then that mask is multiplied by the window and then median is find out and center value is replaced by that median. This filter outperforms the median filter performance in the edge preservation aspect and detail preservation.

Table 1.6. Describing noises found in medical fundus image

Noise type	Description
Gaussian Noise (Amplifier noise)	• Thermal vibration of atoms, amplifier noise and radiation of warm objects are the main cause of the generation of Gaussian noise. • It is also known as white noise or amplifier noise. • It changes the pixel values in digital images. • Gaussian noise spreads evenly on the image and has Gaussian distribution in structure. • The probability distribution function is of bell shape [1] and is expressed by $W(f) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(f-n)^2}{\sigma^2}}$ Here f= gray level n =mean value of Probability density function σ = noise standard deviation

Salt and Pepper Noise (Impulsive noise)	• Also known as intensity spikes, this noise is of impulse type and is caused by error in transmission of data. • This noise is very commonly found in fundus image. • The following expression shows the distribution of impulse noise $f(\mathrm{N}) = \begin{cases} \mathrm{p_a} & \text{for N = a} \\ \mathrm{p_b} & \text{for N = b} \\ 0 & \text{otherwise} \end{cases}$ Where $a, b \in \mathcal{R}$ p_a=Probability of a p_b= Probability of b N= Random Variable

CLAHE technique

Contrast Limited Adaptive Histogram Equalization (CLAHE) is the method to improve the low contrast issue for the digital images especially medical images. Particularly in medical imaging, outperforming results of CLAHE makes it superior than ordinary Histogram Equalization (HE) and Adaptive Histogram Equalization (AHE) [49].CLAHE basically operates by regulating the contrast enhancement that is usually performed by ordinary HE which results in the noise enhancement as well. Therefore by limiting the contrast enhancement in HE, desired results were achieved in the cases where noise become too prominent by enhancing contrast i.e. specifically medical images. Basically contrast enhancement can be stated as the slope of the function that is relating input image intensity value to desired resultant image intensities. Contrast can be limited by limiting the slope of this relating function. Also, contrast enhancement is directly related to the height of the histogram at that intensity value [49]. Therefore, limiting the slope and clipping the height of histogram are both same functions that control contrast enhancement. So user can limit the contrast by specifying the clip limit (i.e. height of histogram) according to the need of the contrast. Figure 1.19 shows the histogram of Figure1.1 before and after CLAHE with clip limit 0.0005.

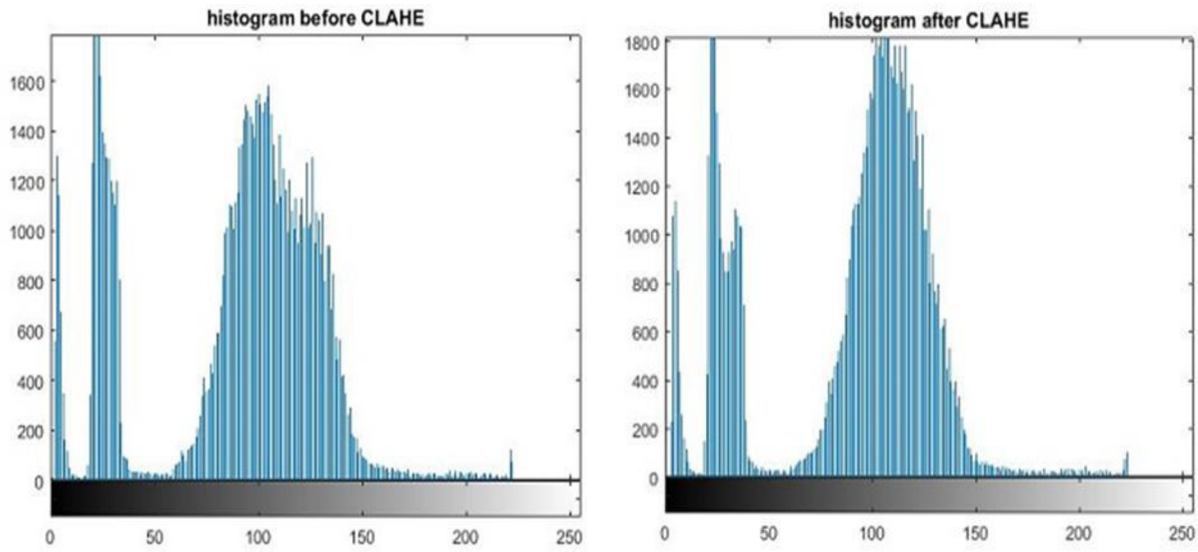


Figure 1.19. Histogram of figure 2.1 before and after CLAHE

CHAPTER 2

LITERATURE SURVEY

This chapter reviews the work done by many researchers in the area of medical image enhancement and fundus image also to increase the perceptivity of image for better accuracy and reliability. Fundus image enhancement and feature extraction is one of the interesting area of interest among researchers now-a-days. So this chapter presents the work done in this area.

2.1 RELATED WORK

Some of the interesting related work is described below and table 3.1 also shows the summary of reviewed work.

Raihan et al. 2015[4] proposed an advanced method of medical image enhancement based on the morphological transformation to improve contrast and quality of image. A disk shaped mask is used in Top-Hat and Bottom-Hat transform and this mask plays a vital role in the operation. The processed images are created by adding the Top-Hat transformation of the original image to the original image and then subtracting the Bottom-Hat transformation from it. The enhanced images have better CNR and PSNR as compared to original image. The newly created images shows better contrast than original one.

Henan et al. in 2011[6] suggested an enhancement algorithm established on multi-scale retinex to be able to improve the strength of remote sensing image enhancement. The principle and recognition types of multi-scale retinex and wavelet were calculated. The research of panchromatic and multicolor remote sensing image enhancement were consented out on the basis of the two methods, the end result display that the mean valve of enhanced image by this algorithm is all about 125, the entropy and definition might be improved by 5% and 25% in contrast to wavelet algorithm, and remote sensing images might gain better enhancement quality, so multi-scale Retinex is a better method for sensing image enhancement.

Yiwen Dou et al. 2017[7] presented an iterative self-adapting color image enhancement based on Chroma and hue constraint to extract visual attention focus in accuracy. In this method, initially the RGB color space should be translated to YCbCr, after that the iteration image enhancement model is applied in constraint of Chroma and hue. Then the remaining image evaluation function implements closed-up control to adjust the iteration step and enhancement performance. When compared to other image enhancement algorithms, ISACIE gives better FO i.e. approx. 97 and has achieved the good performance over traditional methods in low illuminate environment.

Hasikin, Khairunnisa et al. 2012[5] proposed a fuzzy grayscale enhancement technique for image of low contrast. The disgrace of the low contrast image is basically caused by the insufficient lighting during image capturing and thus ultimately produces non-uniform illumination in the image. The fuzzy grayscale image enhancement method is given by exaggerating fuzzy events enclosed in the image. The membership function is then adapted to enhance the image by utilizing power-law transformation and saturation operator. The proposed method composed better quality enhanced image and required minimum processing time in comparison to other methods.

Wang Rui et al. 2017[8] represent an improved method to enhance medical X-ray image based on TV-Homomorphic filter which has a good balance in both brightness adjustment and details enhancement. Homomorphic filter is mostly used to lower the uneven illumination and improve the image quality. Results show that TV-homomorphic filter is effective for medical image enhancement as it can increase the image contrast, highlight the details.

Mohommad F. K et al. [9] in 2012 proposed Bi histogram and Multi Histogram methods. Bi HE approach enhances the contrast without affecting the brightness of the image but it degrade the natural display of image. On the contrary, Multi HE methods conserve the natural display but can't maintain the intensity or contrast. Firstly, the histogram of input image is segmented into different sectors and then HE is applied on every sector. Each section is known as sub-histogram. It decreases the decomposition error of input histogram.

Atyali et al. [10] in 2016 gave a new technique for enhancement of brain cancer detection through image fusion which allows combination of features of different modality images. This Technique is made up of application of Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) based fusion to multi-modality medical images, results in an easy and trustworthy technique to detect cancerous tissues through image fusion. It conserves the original structural information from source image and also enhances the corresponding information from the same.

Wang, Lung-Jen et al. [11] manifest that nonlinear image enhancement may be used to improve the quality of a fuzzy image. The aim of it was to build a successful image classification technique to figure out the very best mix of clipping and scaling parameters by the chance cost method for image enhancement. Experimental results gives idea about the proposed opportunity cost method with image classification for the nonlinear image enhancement achieves a much superior subjective and objective image quality performance as to method utilizing the opportunity cost without image classification and other nonlinear image enhancement methods.

Govind et al. [12] in 2013 proposed an enhanced method of medical image enhancement based on applying averaging method in cluster without distorting the local information. This method is efficient in reducing over-enhancement problem. Firstly, the gray levels are clustered based on certain criteria and then on each such cluster new transformation function is applied. As compares to other native methods, it gives better PSNR value and noise free enhanced image.

Peng et al. [13] in 2013 gives a multi-scales nonlinear image enhancement method of THz image. The THz image has lower contrast and huge noise as the THz radiant power is small, for the purpose of enhancing the image definition. The detail coefficients are captured to de-noise and histogram equalization to be able to improve this is of image edge and image detail. The approximation coefficients are considered for nonlinear transform to be able to suppress the background noise and enhance target information. The proposed method could hike up the prospective information of THz image and withdraw the noise of THz image at the same time. Subsequently the new methodology could boost up the THz image definition, and bypass the incident that the histogram equalization not just improves the prospective information but moreover improves noise. Theory analysis and experiment results that the new method is realistic and efficient, and the THz image enhancement effect is more identical to the character of human eye.

Hossain et al. [14] introduces a method based on nonlinear technique of medical image enhancement and logarithmic transform coefficient histogram matching in 2010. It enhances the visual quality of digital images and also of the images that possess dark shadows because of restricted range of imaging. This method uses EME parameter as a measure of performance. As compared to classic histogram method, this enhanced method gives much better performance regarding visual quality of image particularly those that contain dark shadows like X-ray images.

Selvi M. et al. [15] in 2013 proposed new methodology for fingerprint image enhancement. The initial step in fingerprint recognition is enhancement. The main purpose is to give a noise free image. Initially, the portion of the image altered by noise is analysed and then the enhancement is done on that portion by applying fuzzy based filtering approach and adaptive thresholding. This process consists of four steps namely: Pre-processing, Fuzzy based filtering, Adaptive thresholding, and Morphological Operation. This methodology when compared to existing approaches gives better PSNR values than all these classical methods.

Tiwari et al. [17] proposed enhancement of medical images by preserving the brightness and enhances contrast of image using adaptive gamma correction and homomorphic filtering. It is basically a two-step process: First step enhances the global contrast of image using gamma correction and weighted probability distribution of luminance pixels and then second step is used for image sharpening by homomorphic filtering for preserving image brightness. Results show that this method enhances images with greater PSNR and also it minimises mean brightness error as compared to other methods in processed image.

Khairunnisa et al. [18] have proposed a fuzzy based technique in 2013 for low contrast and non-uniform images. The fuzzy method distinguish the dark and bright portions of the image. The fuzzy based technique surpass the other classical enhancement techniques such as power law transformation. Also, it provide brighter images and takes less time to process as compared to other techniques. Processing time of the Fuzzy approach is proved to be 100ms.

Rajesh et al. [19] in 2016 provides an effective enhancement method to eliminate random impulse noise in images. This technique uses decision tree based method (DTBM) to remove random impulse noise from gray scale images. Firstly the disrupted pixels are identified using Impulse detector and then edge preserving image filter is used to reconstruct the pixels. The experimental result on various images show that the value of PSNR of reconstructed images are better and it effectively remove noise from images.

Bhattacharya et al. [20] have presented a rapid method called singular value decomposition (SVD) to enhance the contrast of an image locally. This technique is used to enhance the visual information of an image using multiple steps such as contrast enhancement, de-blurring, de-noising etc. Contrast Enhancement is the most crucial part of enhancement of image. Mostly, the contrast enhancement techniques rely on the global enhancement of images but such global methods results in the loss of information in images. Thus, a technique is required to enable localized image enhancement.

Qin Xue in 2013 [21] proposed a new methodology for medical image enhancement by imposing local range modification in shearlet domain. Contrast Improvement Index (CII) is used to evaluate the proposed method with other conventional image enhancement method. Local Range Modification (LRM) is a gray-level enhancement technique which is used on shearlet domain to enhance medical images in this methodology.

Liang hua et al. [22] presented a new color medical image enhancement method which fuse together YH transformation and enhanced nonlinear extrapolation algorithm. The color image is disintegrated into ‘chromaticity numbers matrix’ and ‘intensity numbers matrix’. This methodology possess features of perceptivity, briefness, competence, and the processing speed is fast when experimentally computed.

Feng. Zhou et al. [23] propose NSCT (Non-subsampled Contourlet Transform) based medical image enhancement technique. Primarily, NSCT provides a multiresolution and multi-direction analysis for the medical images. Non-subsampled Laplace Pyramids are used to disintegrate the image into different scales, then the non-subsampled directional filterbanks are used to disintegrate the image into different directions and measure the noise variance of each sub-band. Then after that coefficient of each directional sub-band are categorized into strong edges, weak edges and noise by Bayesian classifier. A nonlinear mapping function was deduced to enhance and suppress the different coefficients flexibly to get a good enhancement result with significant characters. When compared to NSWT, this method gives lesser MSE and greater PSNR.

Aggarwal et al. [24] in 2014 proposed a new technique for medical image enhancement that suffer from noise and edges degradation. This technique uses Adaptive Multiscale Product Thresholding for image de-noising and contiguous wavelet sub bands are multiplied to enhance edge structure. Canny Edge Detection Algorithm is applied with scale multiplication technique to enhance edges. This proposed scheme when evaluated by parameters MAE, PSNR and SNR, it gives better results for only for Poisson noise removal.

Jindal et al. [25] presented a new technique in spatial domain to enhance bio-medical images. Enhancement of bio-medical image comprises of techniques like smoothening, edge detection, high-boost filter and power law transform. When applied on dark images like X-Ray image that contain dark patches and shadows, this technique gives better results on the scale of better value of gamma and entropy.

Kurt et al. [26] in 2012 proposed am enhancement technique of medical images which rely on Top-Hat morphological transform, CLAHE and anisotropic filter to improve the contrast and also to enhance the quality of specific visual areas that are of particular interest. When EME (Enhancement measure) of original image and enhanced image was compared, this method gives very beneficial results.

Yelmanova et al. [27] presented an automatic mode contrast enhancement algorithm for images with small size and low contrast based on the histogram equalization for the contrast distribution at the boundaries and background in 2017. There are number of contrast parameters used in this method to evaluate the performance. As a result, this method gives better contrast values than original images.

Rajendran et al. in [33] combines morphological transformation with edge filter to enhance the edge degradation in medical images. This methodology put into use the combination of guided filter with edge enhancement and contrast stretching and hence the results obtained were lesser noise in CT images and X-ray images as compared to some other enhancement method.

Rahim et al. [55] showed three different algorithms for the digital fundus image enhancement for the detection of diabetic retinopathy in the green channel with the help of Histogram Equalization (HE), CLAHE and Mahalanobis Distance (MD) for the improvement of the blood vessels detection in the fundus image. Among the three MD techniques work best in the green channel in this proposed work.

Salem et al. [51] on the other hand showed the importance of red channel along with the green one in the preprocessing of the digital fundus image. In their proposed solution, they used the merging of red and green channel histograms and then compared the sensitivity and specificity of proposed histogram matching solution with standalone green and red channel. Results showed that proposed solution outperformed naive red and green channel computation. Hence red channel is also important in the preprocessing along with green channel.

Nayak et al. [53] used both green and red channel of the fundus image to extract the details that are required to detect glaucoma with the help of fundus image. They applied morphological operations on the different channels to dig out details like cup to disk ratio, blood area of vessels, etc. to classify whether the fundus image have glaucoma or not.

Intajag et al. [56] proposes the method of histogram analysis to improve the contrast and issue of dynamic range in digital fundus image by extracting green channel of the fundus image and then applying histogram partitioning and index of fuzziness logic to the green channel. Experimental results show that the proposed algorithm shows better results than Naive Histogram Equalization (HE).

Hani et al. [57] firstly in 2013 proposed the three variations of adaptive wiener filter to remove additive, multiplicative and combination of both noises in the fundus image. The proposed method showed better PSNR value when filter was applied after retinex algorithm. Later in 2014, Hani et al. [58] proposed an algorithm to enhance fundus image by removing noise from it using time domain constraint estimator (TDCE) and compared it with other algorithms and concluded that the proposed algorithm works more efficiently in expression of PSNR improvement.

Noronha et al. [52] proposed different algorithms to mine different features from fundus image and then combining them again to give more enhanced fundus image that can be used to detect more accurately the abnormalities in the eye. These algorithms extracted the most important features like optic disk, fovea, blood vessels and exudates from fundus image and then combining these extracted features to provide better image for diagnosis.

Setiawan et al. [50] in 2013 used the concept of CLAHE in the green channel of the digital retinal image to improve the contrast and then compared it to classic histogram equalization method of contrast improvement. They also showed that CLAHE works best in standalone green channel as compared to others channels of fundus image and the image after applying CLAHE in green channel was better than applying CLAHE in all channels of fundus image.

Malathi et al. [59] compared various filters like median, wiener, average, gaussian and haar filter on various types of noises like Gaussian, poisson, salt and pepper and speckle noise for fundus image enhancement. They concluded that wiener and haar filter works best for all the noises except salt and pepper noise. Median filter works best for salt and pepper type of noise. Multiple performance parameters like Mean Square Error (MSE), PSNR, Normalized Absolute Error (NAE) and Normalized Cross Correlation (NCC) were used for evaluation of result.

Ref. No.	Proposed Objective	Techniques Used	Results	Other Important Consideration
[2]	Medical image enhancement using morphological transformation.	Top-Hat and Bottom-Hat Transform and morphological transformation	For different radius of masks, CNR and PSNR are higher than original image	As radius of mask increases PSNR decreases and SNR increases considerably
[3]	Low contrast image enhancement using fuzzy set theory	Fuzzy measures and membership functions	Processing time: 0.062 sec , PSNR=22.039	Processing time of proposed method is greater than NINT technique
[5]	Multiscaleretinex (MSR) based image enhancementmethod	MSR enhancement algorithm and Wavelet Transformation	For panchromatic as well as coloured image, higher mean value is obtained and lower entropy and definition	MSR have better effect than wavelet transformation
[6]	Enhancement of color image by iterative and self-adapting method based on Hue and Chroma constraints	Chroma and hue constraint	Focus Overage FO(%)=97 Computational Time=570 ms	Only limited for robot visual servo use
[7]	TV-Homomorphic filter based image enhancement for X-ray image.	Total variation and homomorphic filter	Higher average gradient and laplacian whereas only slight change in values of mean and entropy	
[8]	Image enhancement technique based on histogram equalization for contrast enhancement and brightness preservation.	Histogram equalization	Maximum Standard Deviation (SD) = 27.15 Minimum Absolute Mean Brightness	
[9]	Enhancement technique for brain tumor detection through image fusion	DWT and Principal Component Analysis (PCA)	MSE (max)=1424.44 PSNR (max)=25.21 Structural Content (SC)-(max)=2.17 Standard Deviation (SD)-(max)=80.4 Entropy(max)=1.83	

Table 3.1. Summary of existing medical image enhancement techniques

Ref. No.	Proposed Objective	Techniques Used	Results	Other Important Consideration
[10]	Image enhancement based on combined opportunity cost and image classification for non-linear images	Opportunity cost, NIE algorithm, Optimal parameter combination and image classification	PSNR(max)=33.6757 Mean Opinion Score (MOS)-(max)=4.6 Reliability of -measure(r)=0.78627	
[11]	Enhancement of medical images based on averaging methods in cluster	Averaging Method	PSNR(max)=25.43	Easy to implement and give noise free enhanced image and also remove over-enhancement
[12]	Enhancement of THz image based on the multi-scales non-linear method of enhnacement	Nonlinear filter	Better enhancement and more detailed edges	No quantitative parameter is used to evaluate the results
[23]	Medical image enhancement based on nonlinear technique and logarithmic transform coefficient histogram matching	DCT, logarithmic transformation, HE and orthogonal transformation	Greater value of EME(i.e. 121.71) as compared to original as well as image after applying HE	Can be greatly used for face detection
[24]	Fuzzy based fingerprint enhancement technique based on adaptive thresholding	Fuzzy based filtering, Adaptive thresholding and Morphological operation	Highest PSNR(38.24) as compared to other classical methods	
[27]	Medical image enhnacement based particularly for preserving the brightness and enhancement of contrast	Adaptive gamma correction, Homomorphic filtering and image normalization	Absolute Mean Brightness Error (AMBE)(avg)=1.8792 PSNR(avg)=28.151	Enhances both global as well as local contrast
[28]	Fuzzy image enhancement for low contrast and non-uniform illumination images	Gaussian membership function	Quality Index(Q)=0.92 PSNR=33 Computational Time(s)=0.95	Computational time of algorithm is higher than other methods (i.e. FHE and HE)

Ref. No.	Proposed Objective	Techniques Used	Results	Other Important Consideration
[29]	Image enhancement and de-noising based on removal of random impulse noise in images	Decision Tree and DCT	PSNR(max)=37.41 for 5%noise PSNR(max)=34.43 for 10%noise PSNR(max)=32.53 for 15%noise PSNR(max)=30.92 for 20%noise	As % of noise increases, PSNR falls significantly
[30]	Localized Image Enhancement with the technique of depth map	Depth map and localized image enhancement	PSNR=15.28 Contrast Enhancement Metric(F)=39.79 Image Quality Index (Q)=10.35 Color Enhancement Factor (CEF)=21.33 Computational Time=26.57	Proper illumination model and reflectance model is needed to enhance radiometrically similar objects
[33]	Medical Image Enhancement Based on Non-subsampled Contourlet Transform (NSCT)	No subsampled contourlet transform	Image of spine MSE=621.4015 PSNR=726.322	
[34]	Medical Image Enhancement Using Adaptive Multiscale Product Thresholding	2-D wavelet transform (DWT) and Canny edge detection algorithm	Image of cameraman PSNR=25.0251 SNR_original image=14.5896 SNR_enhanced image=22.1015	For all images under consideration, the proposed technique gives best result for only Poisson noise
[35]	Bio-Medical Image Enhancement using the techniques of spatial domain	Laplacian filter, Histogram equalization and non-linear transformation	Lowest gamma=0.8 Highest entropy=5.4701	This technique can be further enhanced using logarithmic transformation or any other suitable one
[37]	Medical Image Enhancement Based on Histogram to focus particularly on contrast enhancement	Histogram processing	Contrast of image is increased as compared to other methods	

CHAPTER 3

A PROPOSED TECHNIQUE FOR REMOVING NOISE AND IMPROVING CONTRAST OF FUNDUS IMAGE BY COMBINING FILTERING TECHNIQUES BY CLAHE

This chapter presents a proposed technique with integrated filtering and CLAHE based medical fundus image enhancement technique which decomposes RGB fundus image into its individual red, green and blue components, followed by applying filtering technique on them to remove noise and then applying CLAHE for contrast enhancement of each component. Finally these individual components are merged to form overall enhanced RGB fundus image. The proposed model provides de-noising and contrast enhancement at each individual component of fundus image.

3.1 BACKGROUND

Noise and different environmental conditions degrade medical images. Several studied have been proposed in the literature to reduce noise and enhance the quality of medical images. Still there are some researches issues need to be considered shown in figure 3.1. They are discussed below.

Edge degradation: Edges plays most representative role in image processing but image enhancement technique may corrupt the edges too. Therefore it can result in degradation of edges.

Illumination: Maximum number of processes relies upon specific pre-defined norms to concentrate on the objects or regions in particular image. This may cause the “imbalance in the illumination” of the output image after enhancement.

Artifacts: Predominantly image enhancement methods are of “transform domain” type so this may cause certain “artifacts” to occur in output image after enhancement. To get rid of these artifacts, some specific assistance is required.

Lost pixels: Due to transform domain methods of image enhancement, some specific pixels get lost during transformation either "original to transform" or "transformed signal to original pixel values". It is one of the main issue that should be majorly taken into consideration.

Computational complexity: The best technique is that which require minimum computation and hence to minimize computational complexity is one the key factor in image enhancement techniques for its better real-time implementation.

Rahim et al. [55] showed three different algorithms for the digital fundus image enhancement for the detection of diabetic retinopathy in the green channel with the help of Histogram Equalization (HE), CLAHE and Mahalanobis Distance (MD) for the improvement of the blood vessels detection in the fundus image. Out of the three MD techniques work best in the green channel in this proposed work. Most of the researchers take into consideration only the green channel of the fundus image whereas in our proposed algorithm we take into consideration all the channels of the fundus image.

The proposed model provides de-noising and contrast enhancement at each individual component of fundus image. The method tries to overcome the trade off in the performance parameters encountered when using both de-noising and contrast enhancement in all the three channels of fundus image. The major contributions of the proposed work are as follows.

- Individual channels of the RGB fundus image are processed separately and features of these channels are preserved.
- **Improved image contrast:** CLAHE improves the contrast of the image and make detection of abnormalities more particular.
- **Noise Removal:** Proposed method is efficient in removal of almost every type of noise from fundus image and performance parameters shows the positive improvements in the image after the application of proposed method.

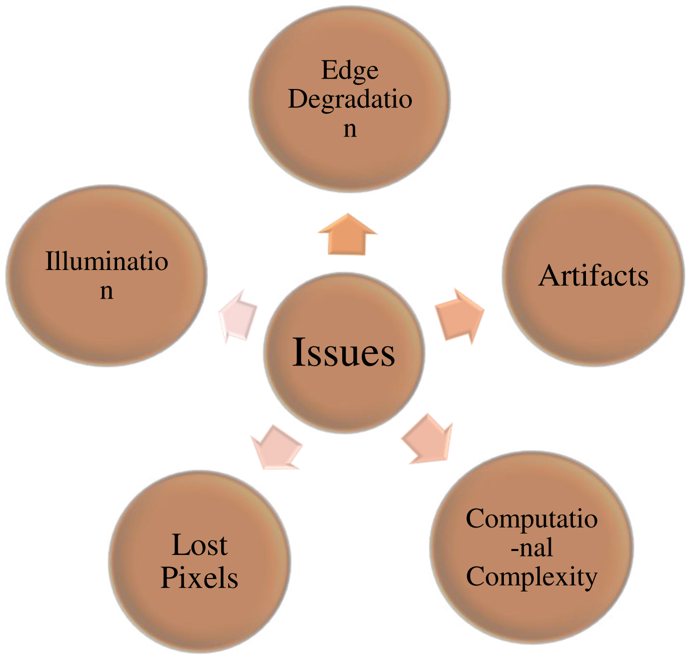


Fig.3.1 showing various prominent research issues in the area of image enhancement

3.2 PROPOSED MODEL AND ALGORITHM

This work presents an integrated filtering and CLAHE based medical fundus image enhancement technique which decomposes RGB fundus image into its individual red, green and blue components, followed by applying filtering technique on them to remove noise and then applying CLAHE for contrast enhancement of each component. Finally these individual components are merged to form overall enhanced RGB fundus image. The proposed model provides de-noising and contrast enhancement at each individual component of fundus image. The method tries to overcome the trade off in the performance parameters encountered when using both de-noising and contrast enhancement in all the three channels of fundus image. In this proposed enhancement method for fundus image, different filtering techniques are used to remove the different types of noise from the red, green and blue channels of image individually at different noise variance levels. Then CLAHE technique is applied on the de-noised components for contrast improvisation and then individual components are merged to form the de-noised RGB fundus image. Detailed diagram of proposed image is shown in figure 3.2. The algorithmic steps for removing noise and enhancing contrast by the proposed method are given below:

STEP 1: Reading noisy fundus image

$$N(x, y) = I(x, y) + \eta(x, y) \quad (12)$$

Where, $N(x, y)$is the noisy fundus image, $I(x, y)$ is the original image and $\eta(x, y)$ is the additional noisy pixels.

STEP 2: Decomposition of fundus image into its red (R), green (G) and blue (B) channel.

STEP 3: Applying filtering technique to remove noise from the individual channel, results R'(denoised red channel), G'(denoised green channel) and B'(denoised blue channel).

STEP 4: Contrast enhancement and smoothening of de-noised image by CLAHE, results R''(denoised and enhanced red channel), G''(denoised and enhanced green channel) and B''(denoised and enhanced)

STEP 5: Merge all the three denoised and enhanced components together to form denoised and enhanced RGB fundus image, $E(x, y)$.

STEP 6: Repeat step 1 to 5 for different types of filters, noises and noise variances.

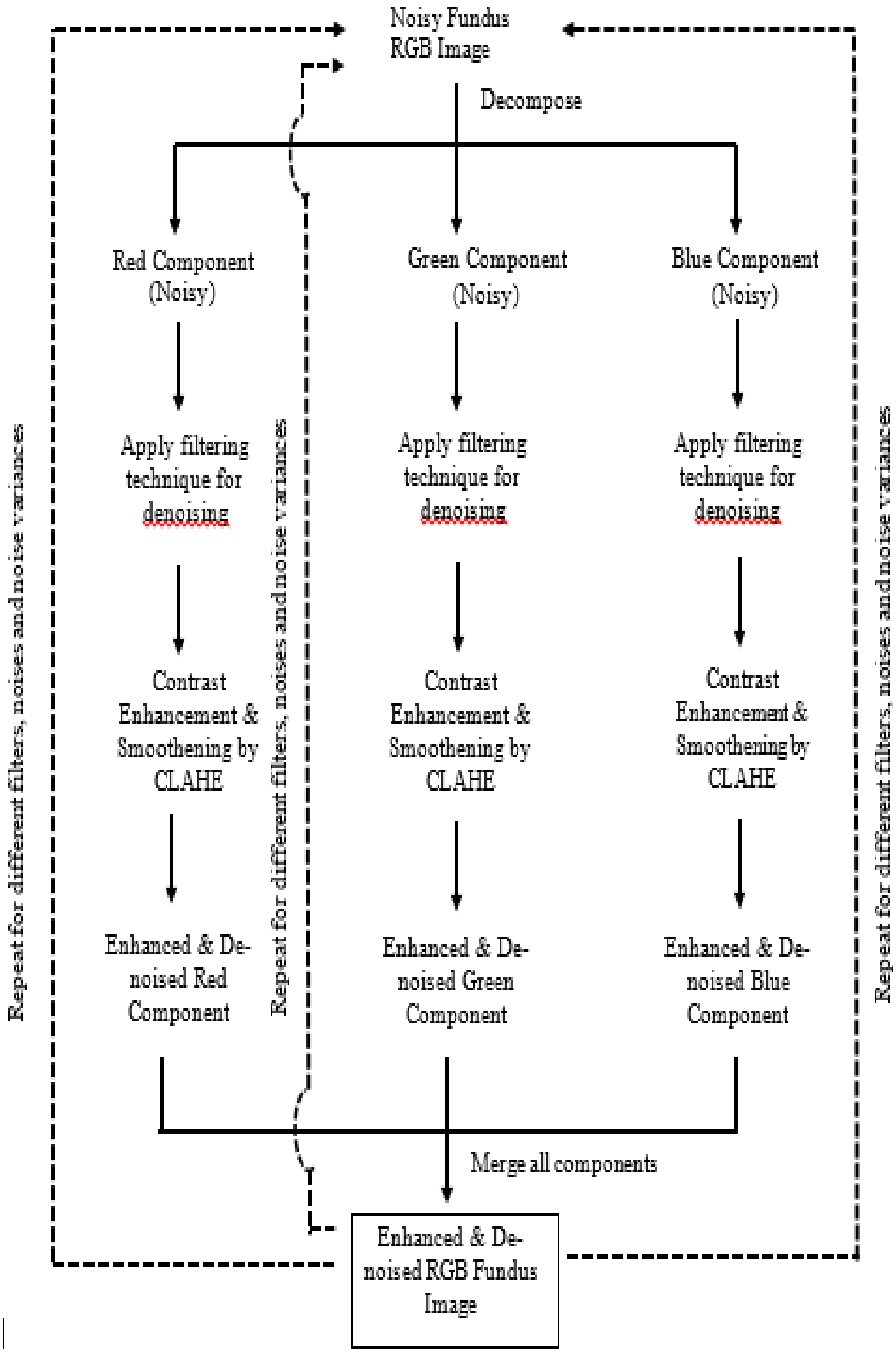


Figure 3.2.Flow diagram of proposed method of enhancement

3.3 METHODOLOGY USED

There are number of steps carried out in the proposed algorithm. This section glorifies the each step carried out in the proposed algorithm.

3.3.1 DECOMPOSITION PROCESS

The very first step of the proposed algorithm is to read the noisy fundus RGB image and then decompose it into individual red, green and blue components respectively. This decomposition of RGB image helps to filter the each component of the noisy image individually and separately as shown in figure 3.3. Figure 3.4a and 3.4b shows the before and after decomposition image of a fundus image respectively.

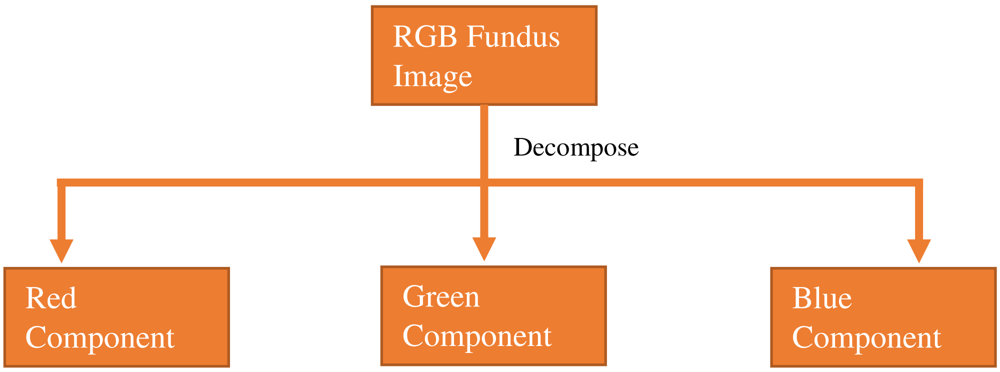


Fig. 3.3 showing decomposition of fundus image

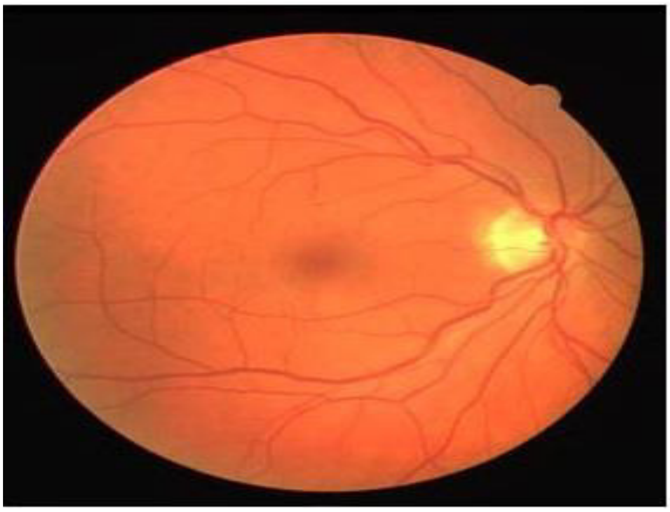


Fig. 3.4a Fundus RGB image before decomposition

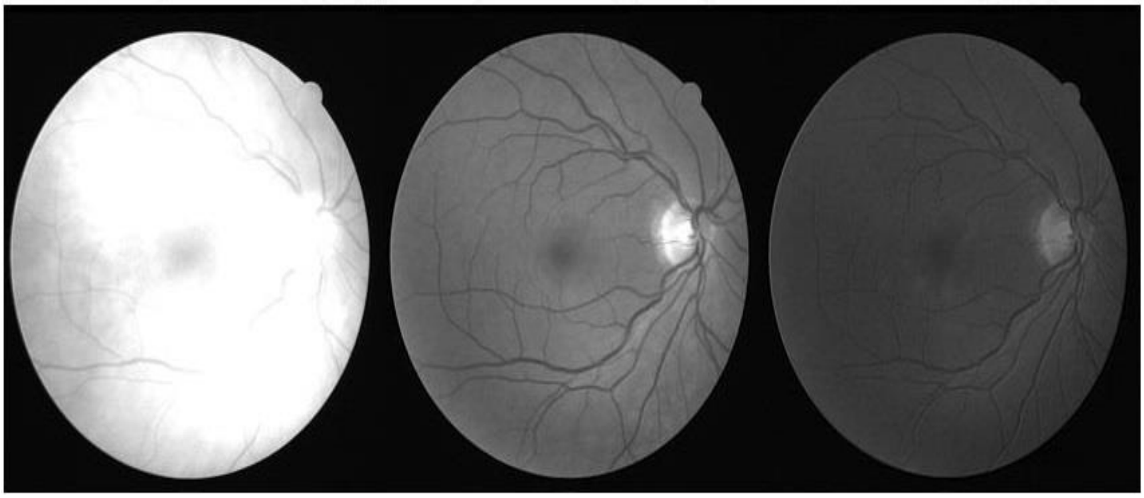


Fig. 3.4b Fundus image after decomposition showing individual red, green and blue component

3.3.2 NOISE FILTERING PROCESS

After the decomposition of fundus image into its respective components, the next step is removal of the noise from the individual components of the image. Filtering process removes the salt and pepper as well as Gaussian noise that prominently occurs in the fundus image. In this proposed model we used many filters and then choose the best one on the basis of different performance parameters. Table 3.1 gives the brief details about the filters that are used in the denoising process. Figure 3.5 shows block diagram of filtering process.

Table 3.1. Describing various filters used in the de-noising of fundus image

Filter Type	Description
Mean Filter or average filter	It is a spatial (linear) filtering technique that replaces the value of pixels in the window with the mean of the pixels value in that window. It is usually used for the purpose of de-noising and smoothening of the image. The noise that mean filter efficiently removes from fundus image is grainy noise. Poor in preservation of useful details in image after noise removal.

Median Filter	It is also a spatial but non-linear filtering technique to remove noise from the image as well as preserve the edge degradation that happens in average filtering. In median filtering, the pixel value that is corrupted is replaced by the median of that window pixel values. Median filter works well for the fundus image enhancement as compared to other linear filters.
Wiener Filter	It is a linear filter that is applied often in frequency domain. Weiner filter is best for the removal of additive noise and blur effect in fundus image. It is also known to be Mean Square Error favorable filter. It works on the noisy signal of the image and outputs the estimate of the original (uncorrupted) image.
Gaussian Filter	It is a linear filter that is used to remove noise from the image along with the blurring of image similar to average filter. It differs from average filter in the aspect that it uses different kernel from mean filter which is in the shape of bell curve (Gaussian PDF). In 2-Dimensional, Gaussian has the equation: $G'(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$ Here mean is (0,0) and σ^2 is the variance (default 1).

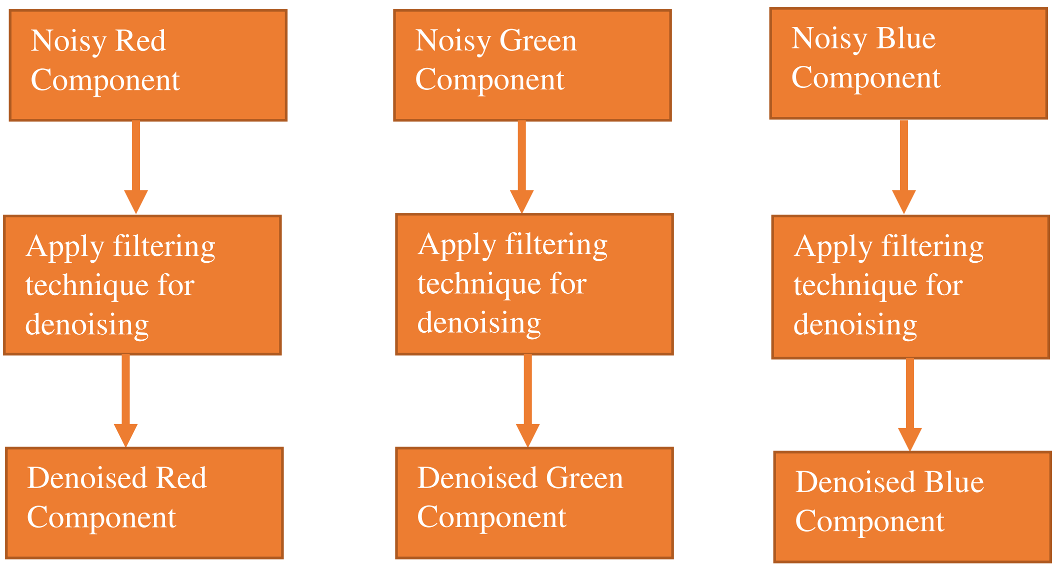


Fig. 3.5 showing denoising step of the proposed model

3.3.3 CONTRAST ENHANCEMENT BY CLAHE

After noise removal, next step is to enhance the contrast of the fundus image by Contrast Limited Adaptive Histogram Equalization (CLAHE) technique. CLAHE is also applied on the individual component of the fundus image and then after CLAHE each component is merged back to form overall enhanced RGB fundus image. Figure 3.6 shows the block diagram of steps carried out in this phase.

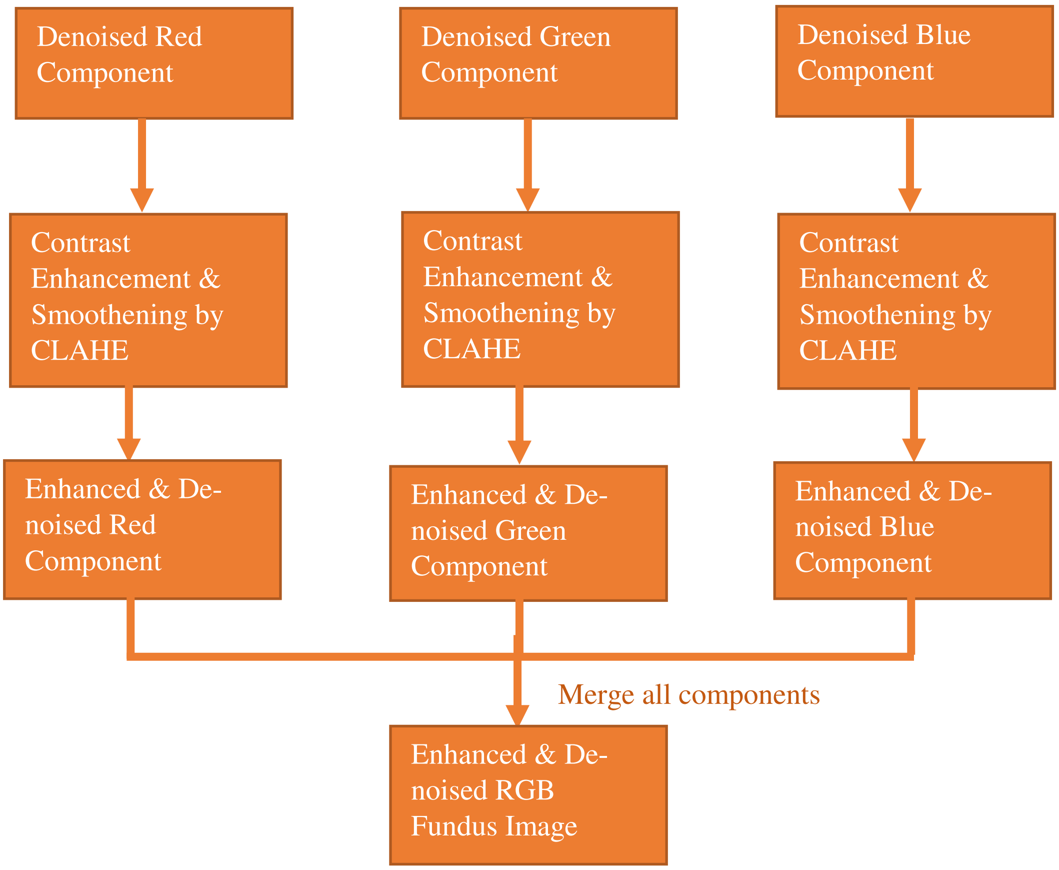


Fig. 3.6 showing steps carried out while and after CLAHE technique

3.4 PERFORMANCE ANALYSIS PARAMETERS

Performance parameters are used to find the quantitative as well as qualitative aspect of proposed algorithm. The performance parameters used to evaluate the efficiency are Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Correlation coefficient (CoC). PSNR is one of the most popular and trustworthy performance parameter used in the evaluation of image enhancement and other areas also. Higher the values of PSNR, SSIM and CoC, better the quality of image and ultimately better the performance of the algorithm. These parameters are demarcated as follows.

3.4.1 PEAK SIGNAL TO NOISE RATIO (PSNR)

As the name explains, it is the ratio of the maximum/peak value of the signal to the noisy signal value. PSNR formally describes the quality of the reconstructed image after the application of any technique on it. Higher the PSNR, better the quality of reconstructed image. The acceptable range of PSNR is 28 dB to 50 dB.

PSNR is defined by:

$$PSNR = 10\ \log_{10} \frac{(Peakvalue)^2}{MSE} \tag{13}$$

Where, peakvalue is the maximum difference in the input image value and MSE is Mean Square Error and is computed as

$$\text{MSE} = \frac{1}{m \times n} \sum_{i=1}^{m \times n} (\hat{y}(i,j) - y(i,j))^2 \tag{14}$$

Where $m \times n$ is the size of the image, $\hat{y}(i,j)$ is the recovered image and $y(i,j)$ is the Original image.

3.4.2 STRUCTURAL SIMILARITY INDEX (SSIM)

SSIM is a quantitative measure to evaluate image quality. It fundamentally measures the amount of similarity between the original image and enhanced image. Higher the value of SSIM, more the images are structurally identical. SSIM is formulated as:

$$\text{SSIM}(\text{X}, \text{Y}) = \left[l(\text{X}, \text{Y})^{\alpha} . \text{c}(\text{X}, \text{Y})^{\beta} . \text{s}(\text{X}, \text{Y})^{\gamma} \right] \tag{15}$$

Where 'X, Y' are two windows of same dimension of original and reconstructed image respectively. α, β, γ are the weights assigned to these parameters and l, c and s are the luminance, contrast and structure respectively, which together combine with certain weights to form SSIM and are computed as

$$l(X,Y) = \frac{2\mu_X \mu_Y + c_1}{\mu_X^2 + \mu_Y^2 + c_1} \tag{16}$$

$$c(X,Y) = \frac{2\sigma_X \sigma_Y + c_2}{\sigma_X^2 + \sigma_Y^2 + c_2} \tag{17}$$

$$s(X,Y) = \frac{\sigma_{XY}+c_3}{\sigma_X\sigma_Y+c_3} \tag{18}$$

Here 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,σ_{XY} is the co-variance of X and Y,c_1 and c_2 are the two parameters to stable the division with poor denominator and$c_3 = \frac{c_2}{2}$. When value of SSIM approaches to 1 it shows perfect similarity among initial image and enhanced image.

3.4.3 Correlation Coefficient (CoC)

CoC is responsible to deduce the interdependence among the initial degraded image and enhanced image after application of algorithm. CoC have unit value for the perfect correlation between the two images under consideration. CoC is mathematically expressed as:

$$CoC_{X,X'} = \frac{\left(E\left[(X-\rho_X).(X'-\rho_{X'})\right]\right)}{\sigma_x\sigma_{X'}} \tag{19}$$

Where $\rho_X$and $\rho_{X'}$ are the average of the original and recovered images,$\sigma_x$and$\sigma_{X'}$are standard deviation of original and recovered image.

3.5 IMPLEMENTATION AND RESULTS

Proposed algorithm is applied on two databases STARE [62] and DRIVE [61]. Efficacy of the givenmethod is evaluated by the measures of performance parameters i.e. PSNR, SSIM and CoC. Following section illustrates the results obtained by subsequent use of algorithm on images from both datasets.

3.5.1 IMPLEMENTATION AND RESULTS FROM DATASET 1 [62]

Firstly proposed method is applied on the image 3.7 taken randomly from the STARE database. Figure 3.8 shows the medical fundus image enhancement, undergoing each phase of the proposed model step by step with salt and pepper noise, at 0.01 noise value level and noise is removed by using median filter with CLAHE method. Similarly simulation is performed for Gaussian noise present in fundus image against all kinds of filtering techniques of different noise variances, to get the performance of the filtering against different noise types for fundus image. Figure 3.9 illustrates the histograms of individual components afore and later enhancement of the image given in figure 3.7. Performance parameters are evaluated to carry out the efficacy of given solution. The performance parameters used here to evaluate the efficiency are Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Correlation coefficient. PSNR is one of the among most widely used and trustworthy performance parameter present in the area of evaluation of image enhancement and other areas also. Higher the values of PSNR, SSIM and CoC, better the quality of image and ultimately better the performance of the algorithm.

Table 3.2 illustrates the PSNR values for different filtering techniques with CLAHE for different attacks or noises at different noise variances values. This table indicated that the median filter and the weighted median filtering technique is showing approx. equal results with CLAHE for all types of noises but not for Gaussian noise. Weighted median filter presents the acceptable value of PSNR. Figure 3.10 illustrates the graph of PSNR values for different noises against different filtering techniques for 0.001 noise value. From figure 3.10, it is clear that the highest PSNR is 35.37687 obtained with median filtering technique against salt and pepper noise with 0.001 noise level.

Fig. 3.7 Fundus image for experimental results from STARE database

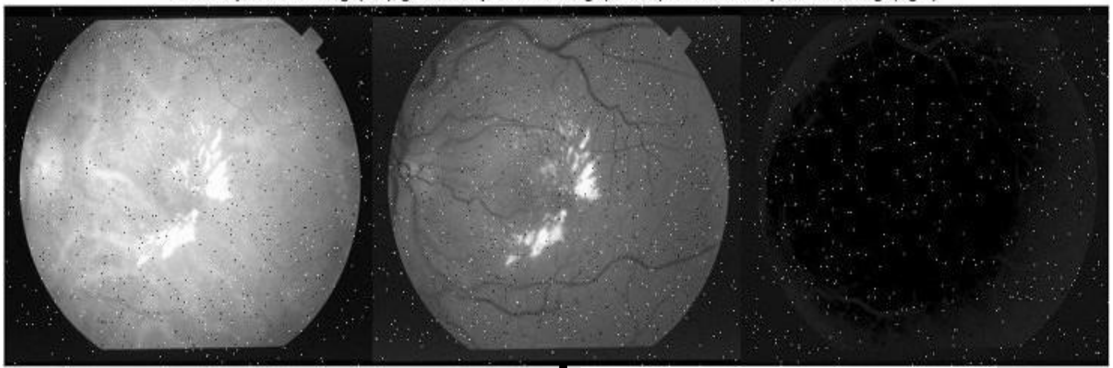
Table 3.2. Showing PSNR values for different filters with CLAHE against different attacks or noises at different noise variance.

Noise Type / Filters + CLAHE	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	35.376870	29.205802
	0.01	35.342524	27.890991
Weiner Filter + CLAHE	0.001	32.783764	28.612019
	0.01	28.545231	27.424313
Average Filter + CLAHE	0.001	32.075036	28.866618
	0.01	31.059567	27.656338
Gaussian Filter + CLAHE	0.001	33.921009	24.371021
	0.01	29.783372	23.836875
Weighted Median Filter + CLAHE	0.001	34.719707	29.718484
	0.01	33.819953	29.329734

Salt and Pepper Noisy RGB fundus image

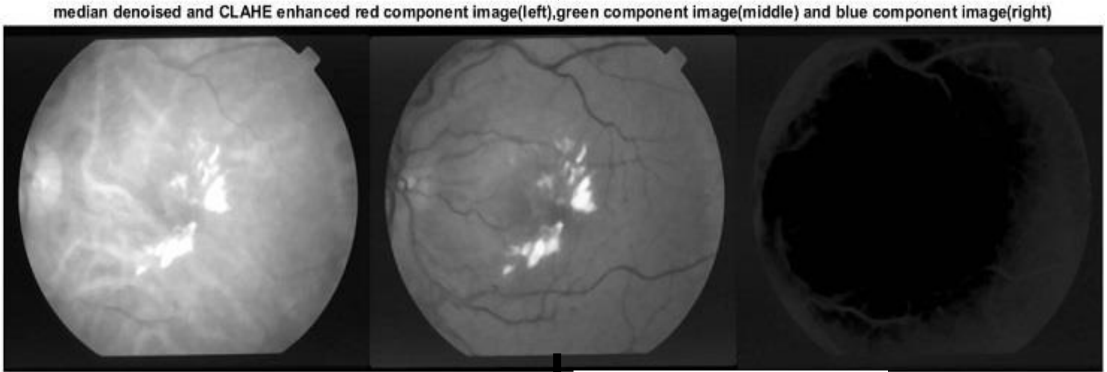
Decompose

red component of image(left), green component of image(middle) and blue component of image(right)



Apply median filter and CLAHE on each individual component

median denoised and CLAHE enhanced red component image(left),green component image(middle) and blue component image(right)



Merge all de-noised and enhanced components

median and CLAHE enhanced rgb fundus image

Figure 3.8. Showing the enhancement of fundus image (Fig. 5.2) by proposed algorithm

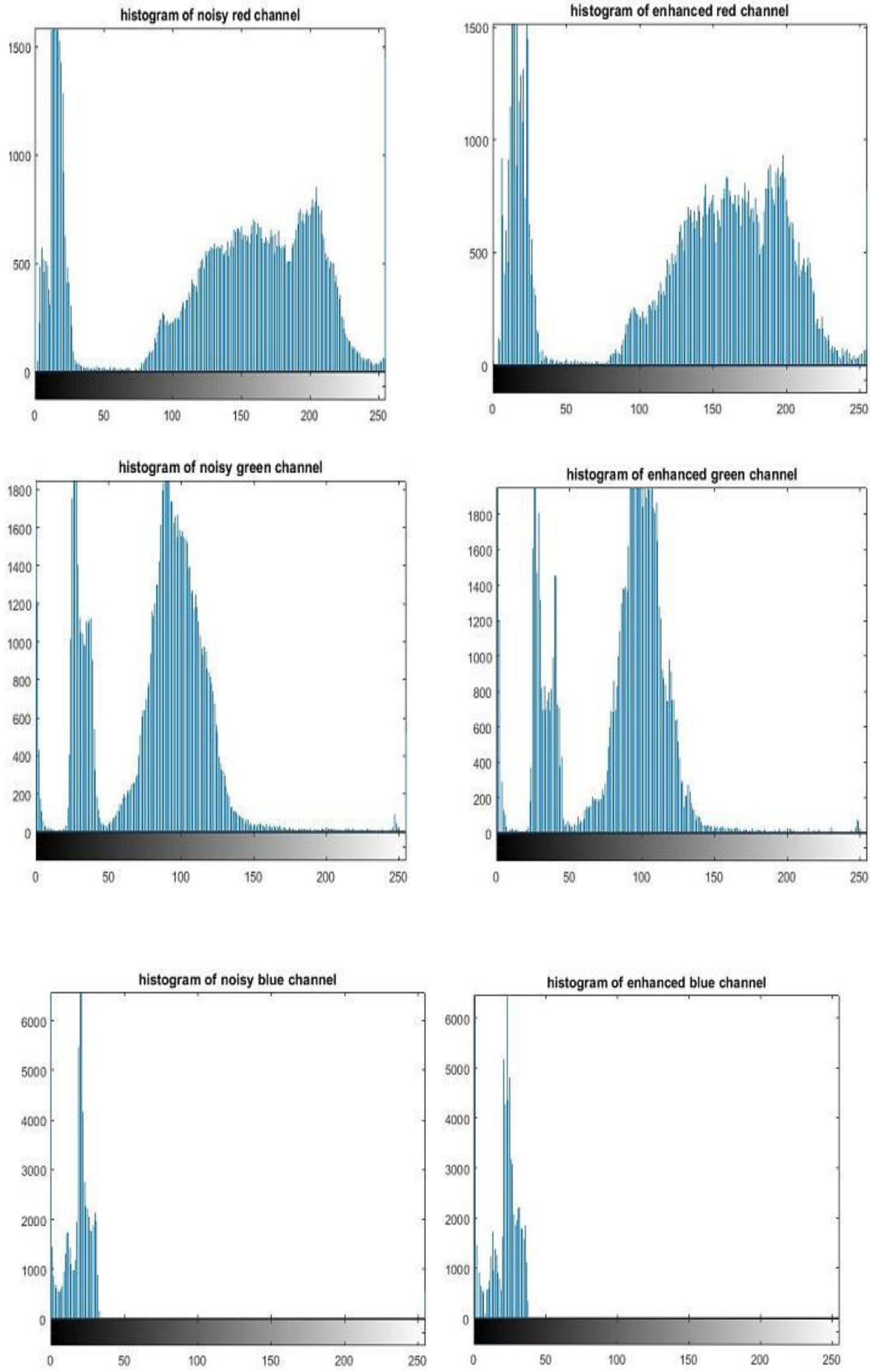


Figure 3.9. Showing the histograms of fundus image components before and after enhancement

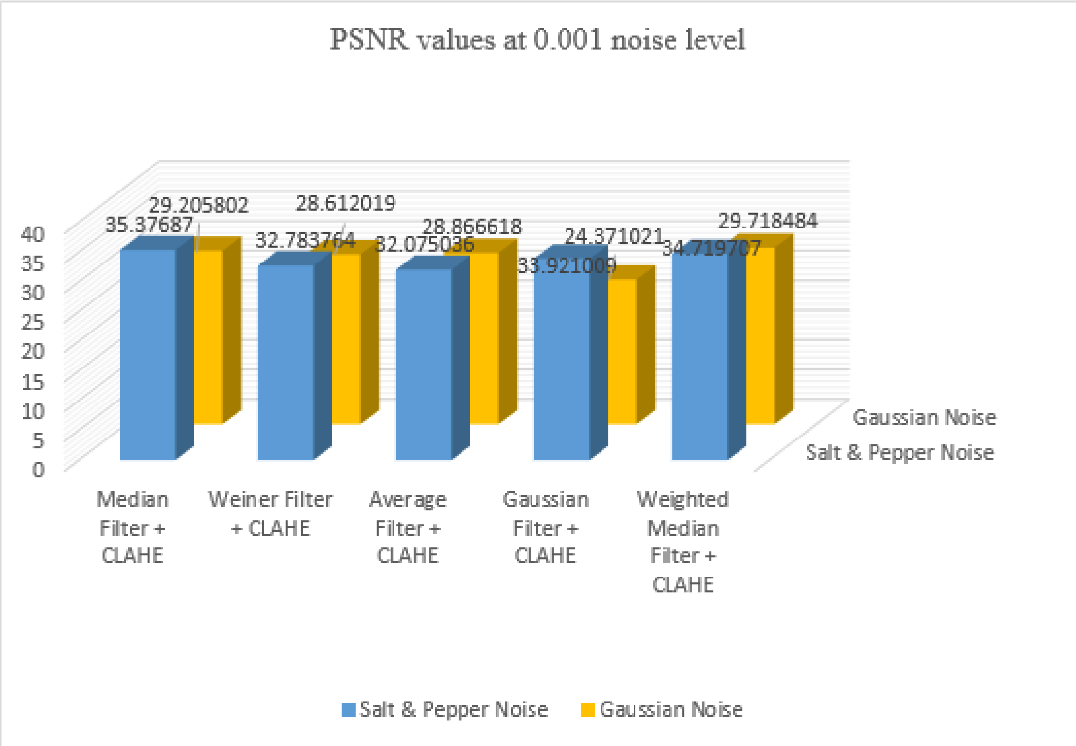


Figure 3.10 Showing PSNR values for different noises against different filters for 0.001 noise level

Table 3.3 displays the value of SSIM for the proposed algorithm against various noises, filtering techniques and noise variances. Figure 3.11 shows SSIM values for different filtering techniques against different noises at 0.001 noise levels. This figure depicts that at noise level 0.001 Median filter and Gaussian filter have greatest SSIM, 0.962327 and 0.962614 respectively for salt and pepper noise.

Table 3.3. Showing SSIM values for different filters with CLAHE against different attacks or noises at different noise variances

Noise Type / Filters + CLAHE	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	0.962327	0.772254
	0.01	0.962192	0.767369

Weiner Filter +	0.001	0.916593	0.755744
CLAHE	0.01	0.736117	0.750255
Average Filter +	0.001	0.926023	0.816556
CLAHE	0.01	0.895237	0.810642
Gaussian Filter +	0.001	0.962614	0.378019
CLAHE	0.01	0.791894	0.374464
Weighted Median	0.001	0.955304	0.727873
Filter + CLAHE	0.01	0.945923	0.721606

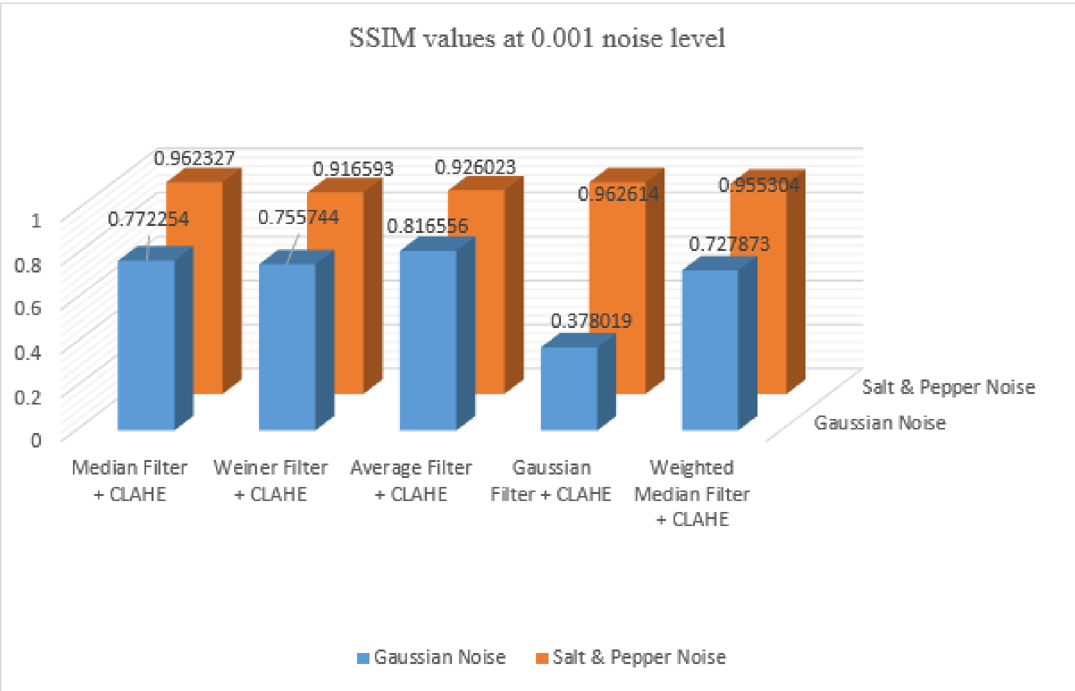


Figure 3.11. Showing SSIM values for different filters against different noises at 0.001 noise level

Table 3.4 shows the CoC values for the given model against various filters, noises and noise variances. Figure 3.12 shows the graph of CoC values at 0.001 noise value. It shows that at noise level 0.001, median filter and weighted median filter have highest CoC, 0.995936 and 0.994919 respectively for salt and pepper noise.

Table 3.4. Showing CoC values for different filters with CLAHE against different attacks or noises at different noise variances

Noise Type / Filters + CLAHE	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	0.995936	0.984200
	0.01	0.995904	0.983187
Weiner Filter + CLAHE	0.001	0.992425	0.985162
	0.01	0.978108	0.984797
Average Filter + CLAHE	0.001	0.991667	0.987125
	0.01	0.989854	0.986607
Gaussian Filter + CLAHE	0.001	0.994516	0.947788
	0.01	0.984102	0.947453
Weighted Median Filter + CLAHE	0.001	0.994919	0.981838
	0.01	0.993559	0.981312

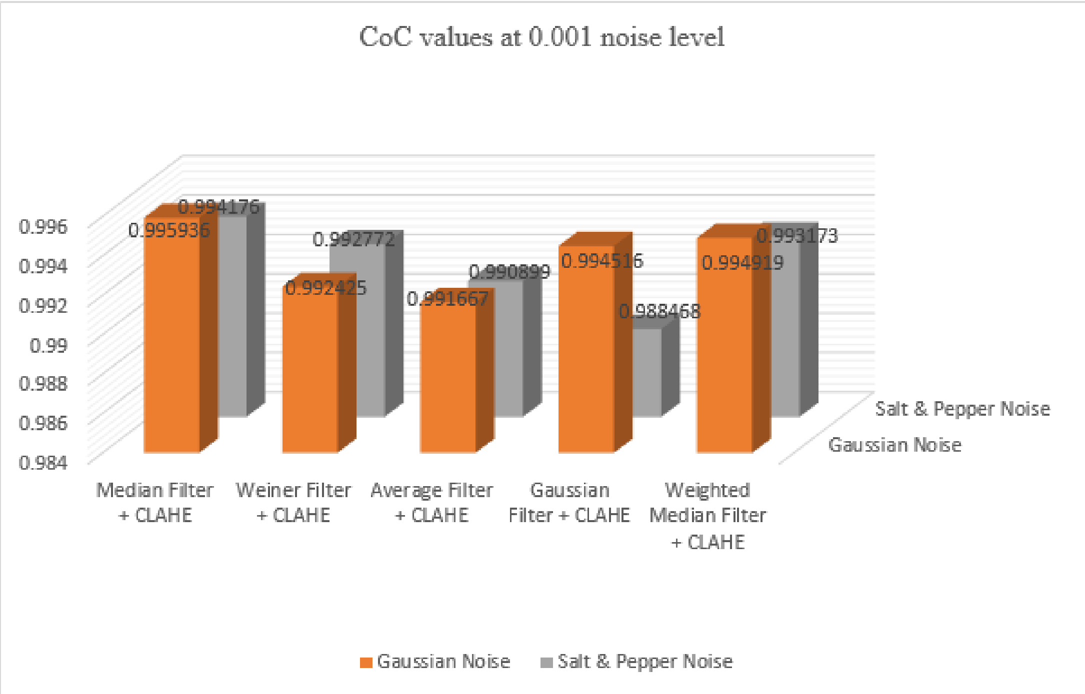


Figure 3.12. Showing CoC values at 0.001 noise level

The efficacy of the proposed algorithm is valued by simulating RGB fundus image at two different noise levels 0.001 and 0.01. Then quality parameters are obtained i.e. SSIM and CoC from fundus image and formulated in table 3.3 and table 3.4 respectively. It is noticeable that out of all the filters used in the proposed model, Median and weighted median filters show outperforming results than other filters for all the noise type at each noise levels. Table 3.5 give the comparison between CLAHE and proposed model against salt and pepper at noise level 0.001.On comparison with simple CLAHE technique, it is clear from table 3.5 that the given method gives outperforming outputs than simple CLAHE technique specially Median filter with CLAHE gives the outperforming results in all spheres. Figure 3.13, 3.14 and 3.15 shows the comparison between proposed technique and CLAHE on the basis of PSNR, SSIM and CoC respectively.

Table 3.5. Showing comparison between CLAHE and proposed model against salt and pepper noise at noise level 0.001

Techniques / Performance Parameters	CLAHE	Median Filter + CLAHE	Gaussian Filter + CLAHE	Weighted Median Filter + CLAHE	Weiner Filter + CLAHE	Average Filter + CLAHE
PSNR	33.347485	35.376870	33.921009	34.719707	32.783764	32.075036
SSIM	0.952207	0.962327	0.962614	0.955304	0.916593	0.926023
CoC	0.993312	0.995936	0.994516	0.994919	0.992425	0.991667

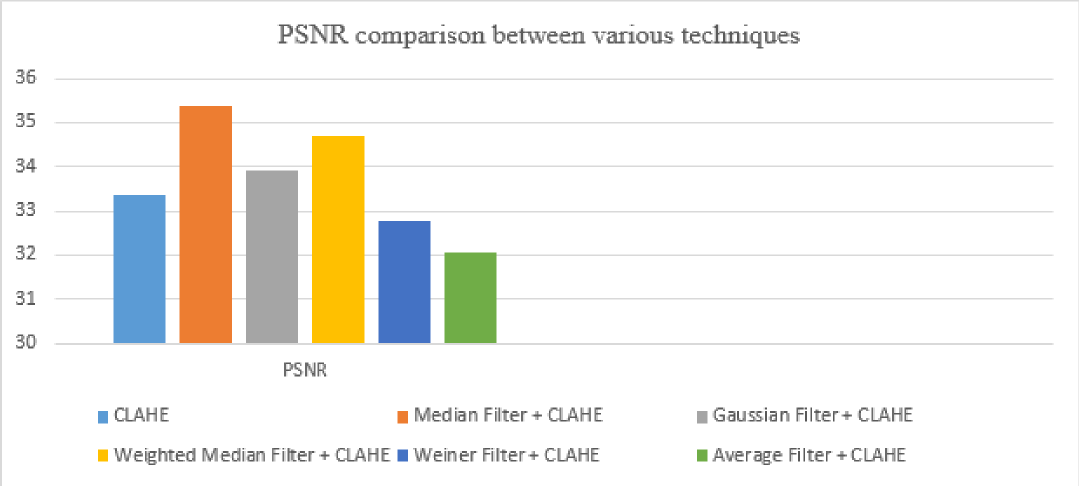


Figure 3.13. Showing comparison between CLAHE and proposed algorithm in terms of PSNR

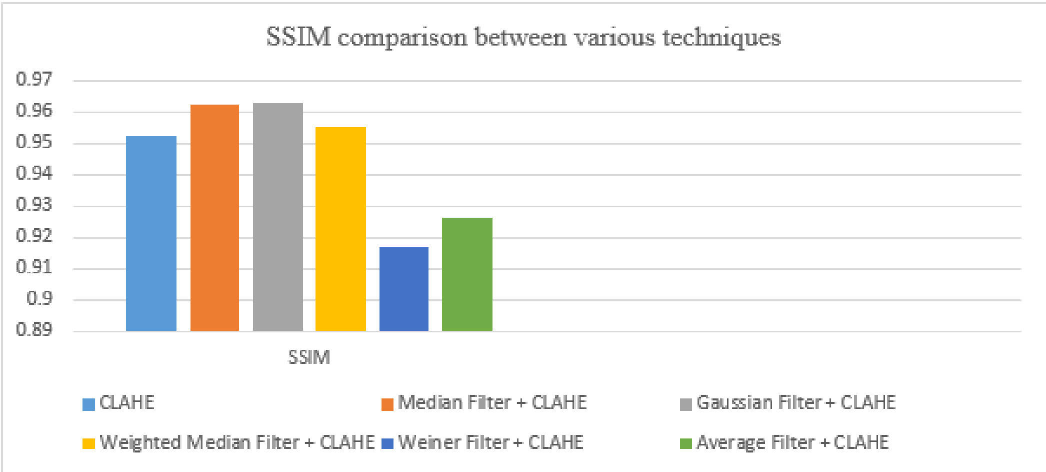


Figure 3.14. Showing comparison between CLAHE and proposed algorithm in terms of SSIM

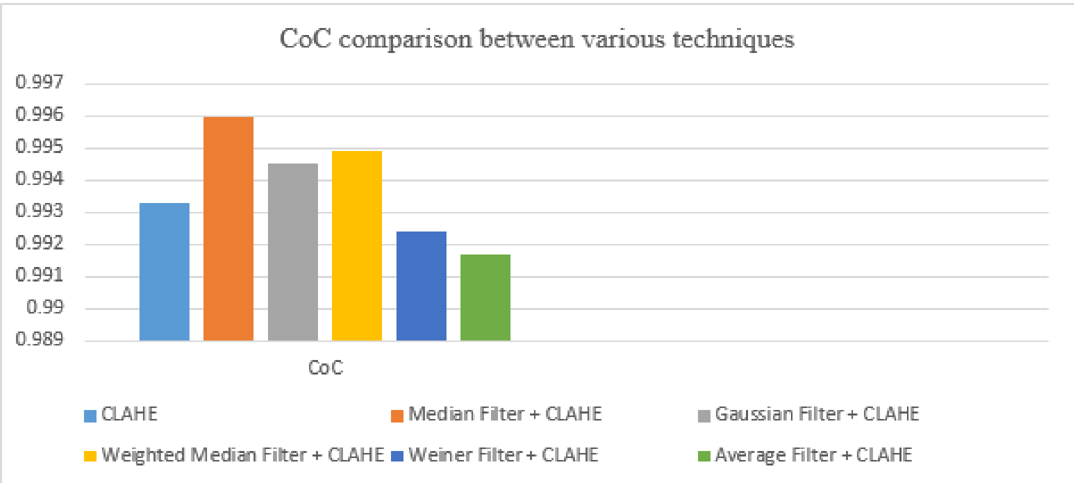


Figure 3.15. Showing comparison between CLAHE and proposed algorithm in terms of CoC

On analyzing, it is found out that the proposed method on dataset 1 gives 6.086% improvement in PSNR, 1.092% improvement in terms of SSIM and 0.2642% improvement in CoC when compared to CLAHE method.

5.4 IMPLEMENTATION AND RESULTS FROM DATASET 2 [61]

For further performance analysis of the proposed algorithm, experimental results were carried out on another dataset i.e. DRIVE database. Figure 3.16 is randomly chosen from DRIVE database and then proposed algorithm is evaluated on it.

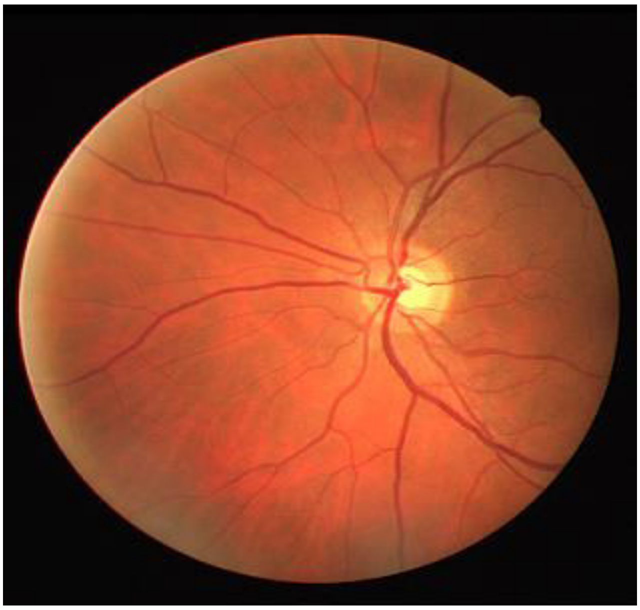


Fig. 3.16 Fundus image for experimental results from DRIVE database

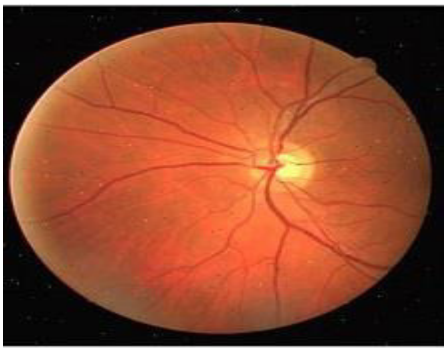
Figure 3.17 shows stepwise enhancement of fundus image of the proposed algorithm with salt and pepper noise, at 0.001 noise variance level and de-noised using median filtering with CLAHE method. Same simulation is done for Gaussian noise found in fundus image against all types of filters of different noise variances.

Figure 3.18 shows the histograms of individual components before and after enhancement of the image given in figure 3.17. Performance parameters are used to find the efficacy of proposed algorithm. The performance parameters used to evaluate the efficiency are Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Correlation coefficient (ρ).

Table 3.6 shows the PSNR values for multiple filtering techniques with CLAHE against different attacks or noises at different noise variances level. The table indicated that the median filter and weighted median filter shows approx equal results with CLAHE against all types of noises except for Gaussian noise. Weighted median filter gives the acceptable value of PSNR. Figure 3.19 shows the graph of PSNR values for different noises against different filters for 0.001 noise level.

Table 3.7 shows the value of SSIM for the proposed algorithm against various noises, filters and noise variances. Figure 3.20 shows SSIM values for different filters against different noises at 0.001 noise levels.

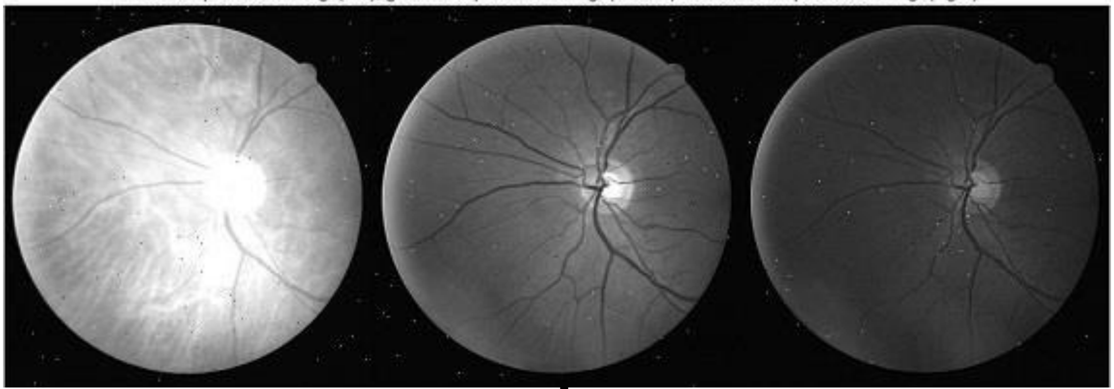
Table 3.8 shows the CoC values for the proposed model against various filters, noises and noise variances. It concluded that median filter and weighted median filter gives best results at every noise variance level for each type of noise. Figure 3.21 shows the graph of CoC values at 0.001 noise variance.



Salt and Pepper Noisy RGB fundus image

Decompose

red component of image(left), green component of image(middle) and blue component of image(right)



Apply median filter and CLAHE on each individual component

median denoised and CLAHE enhanced red component image(left),green component image(middle) and blue component image(right)

Merge all de-noised and enhanced components

median and CLAHE enhanced rgb fundus image

Figure 3.17. Showing the enhancement of fundus image (Fig. 5.11) by proposed algorithm

Table 3.6. Showing PSNR values for different filters with CLAHE against different attacks or noises at different noise variance

Noise Type / Filters + CLAHE	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	35.501158	30.109267
	0.01	35.408863	28.859581
Weiner Filter + CLAHE	0.001	34.463706	28.733831
	0.01	28.976755	27.764810
Average Filter + CLAHE	0.001	30.466448	27.647018
	0.01	29.882077	26.856269
Gaussian Filter + CLAHE	0.001	36.044842	24.907945
	0.01	30.254620	24.358833
Weighted Median Filter + CLAHE	0.001	33.283816	29.582890
	0.01	32.683530	29.521270

The efficacy of the proposed algorithm is weighed by simulating RGB fundus image at two different noise variances i.e. 0.001 and 0.01. Then quality parameters are obtained i.e. SSIM and CoC from fundus image and tabulated in table 5.6 and 5.7 respectively. Table 3.9 shows the comparison between CLAHE and proposed model against salt and pepper noise at noise level 0.001. Figure 3.22, 3.23 and 3.24 "shows the comparison between proposed technique and CLAHE on the basis of PSNR, SSIM and CoC respectively. It is clear from the graphs of figure 3.22, 3.23 and 3.24 that the proposed algorithm gives outperforming results than simple CLAHE technique".

On analyzing, it is found out that the proposed method on dataset 2 gives 3.6162% improvement in PSNR, 1.1941% improvement in terms of SSIM and 0.082% improvement in CoC when compared to CLAHE method.

Table 3.7. Showing SSIM values for different filters with CLAHE against different attacks or noises at different noise variances

Filters + CLAHE \ Noise Type	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	0.923379	0.746510
	0.01	0.922889	0.723251
Weiner Filter + CLAHE	0.001	0.892153	0.698821
	0.01	0.723868	0.688277
Average Filter + CLAHE	0.001	0.875950	0.719070
	0.01	0.835778	0.707905
Gaussian Filter + CLAHE	0.001	0.954826	0.397555
	0.01	0.784526	0.389608
Weighted Median Filter + CLAHE	0.001	0.911820	0.708741
	0.01	0.905161	0.709828

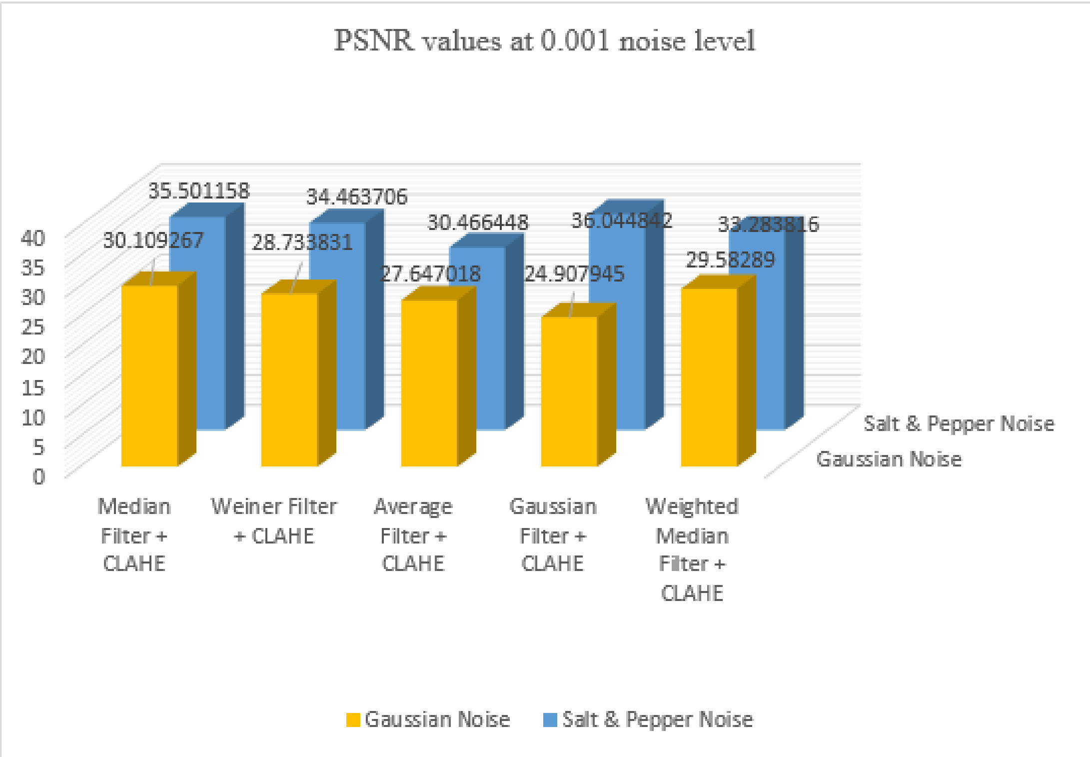


Figure 3.19 Showing PSNR values for different noises against different filters for 0.001 noise level

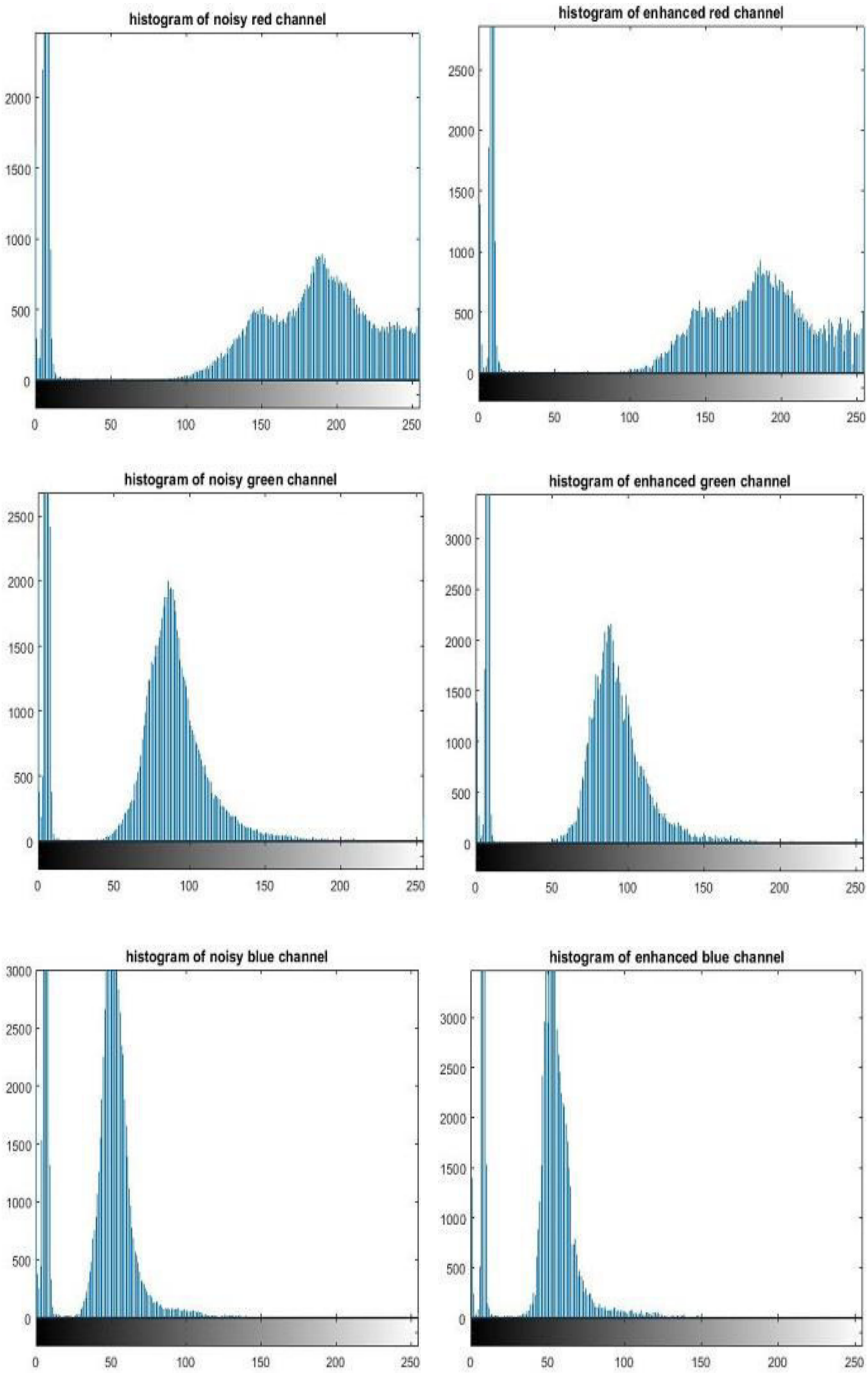

histogram of noisy red channel
histogram of enhanced red channel
histogram of noisy green channel
histogram of enhanced green channel
histogram of noisy blue channel
histogram of enhanced blue channel

Figure 3.18. Showing the histograms of fundus image components before and after enhancement

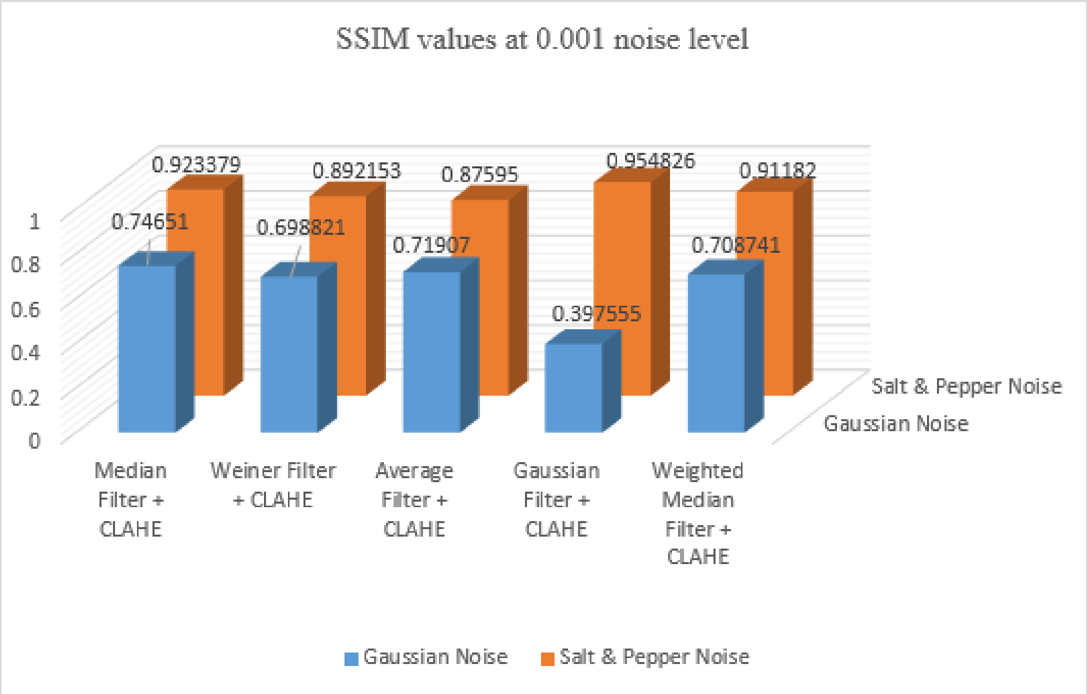


Figure 3.20. Showing SSIM values for different filters against different noises at 0.001 noise level

Table 3.8. Showing CoC values for different filters with CLAHE against different attacks or noises at different noise variances

Noise Type / Filters + CLAHE	Noise Variance	Salt & Pepper Noise	Gaussian Noise
Median Filter + CLAHE	0.001	0.997463	0.991171
	0.01	0.997399	0.990686
Weiner Filter + CLAHE	0.001	0.996655	0.992006
	0.01	0.987349	0.991987
Average Filter + CLAHE	0.001	0.991421	0.988937
	0.01	0.990581	0.988899
Gaussian Filter + CLAHE	0.001	0.998102	0.973263
	0.01	0.991285	0.973402
Weighted Median Filter + CLAHE	0.001	0.995191	0.988795
	0.01	0.994464	0.988356

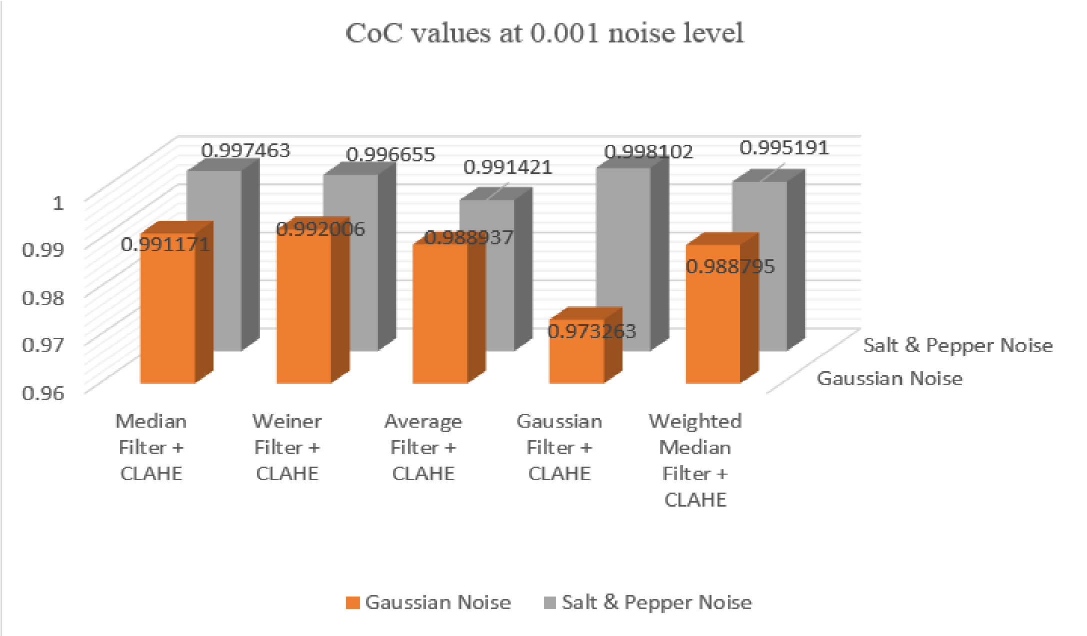


Figure 3.21. Showing CoC values at 0.001 noise level

Table 3.9. Showing comparison between CLAHE and proposed model against salt and pepper noise at noise level 0.001

Techniques / Performance Parameters	CLAHE	Median Filter + CLAHE	Gaussian Filter + CLAHE	Weighted Median Filter + CLAHE	Weiner Filter + CLAHE	Average Filter + CLAHE
PSNR	34.786888	35.501158	36.044842	33.283816	34.463706	30.466448
SSIM	0.943559	0.923379	0.954826	0.911820	0.892153	0.875950
CoC	0.997288	0.997463	0.998102	0.995191	0.996655	0.991421

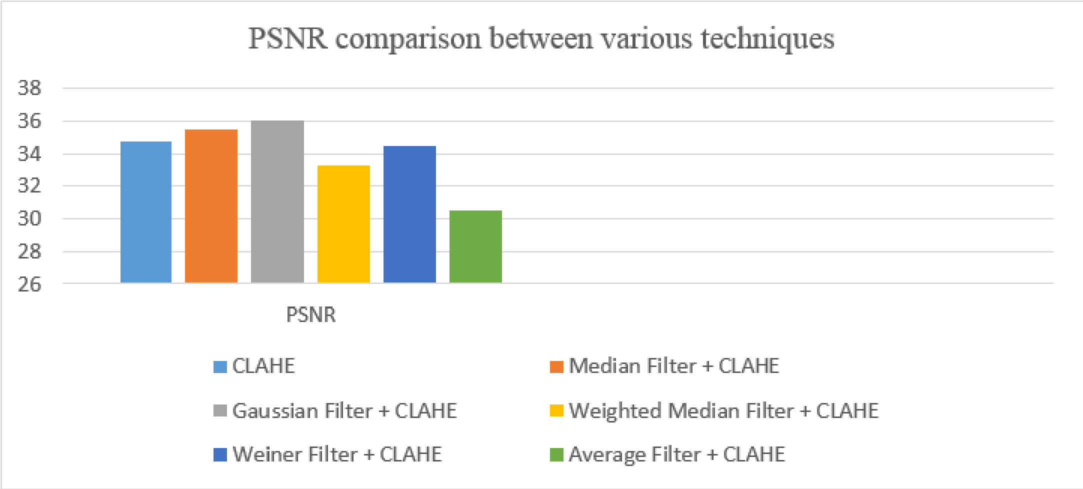


Figure 3.22. Showing comparison between CLAHE and proposed algorithm in terms of PSNR

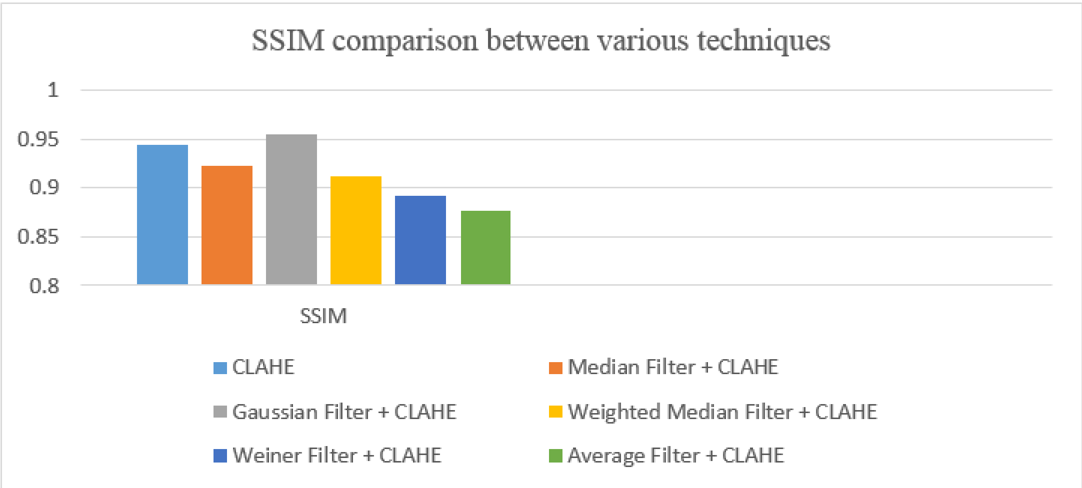


Figure 3.23. Showing comparison between CLAHE and proposed algorithm in terms of SSIM

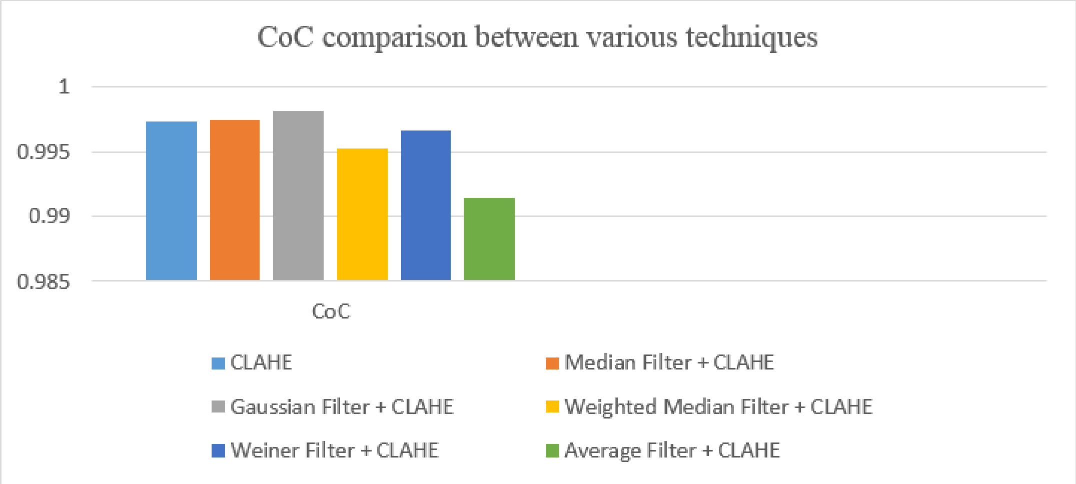


Figure 3.24. Showing comparison between CLAHE and proposed algorithm in terms of CoC

CHAPTER 4

A BRIEF INTRODUCTION TO SIMULATION TOOL AND DATABASES

4.1 TOOL USED – MATLAB R2016a

MATLAB acronym for MATrix LABoratory is a potent tool for the numerical calculation, visualization and programming, modeling and simulation, image processing and many more. It is a fourth generation programming language. Developed by Mathworks, it is globally used for many purposes. Image processing is one of the feature of MATLAB. It is the most common tool used for image processing as its elementary data element is matrix. Also MATLAB validates nearly all computational platform.

Features of MATLAB

MATLAB have numerous features associated with it. Figure 5.1 shows the specific features among them [60].

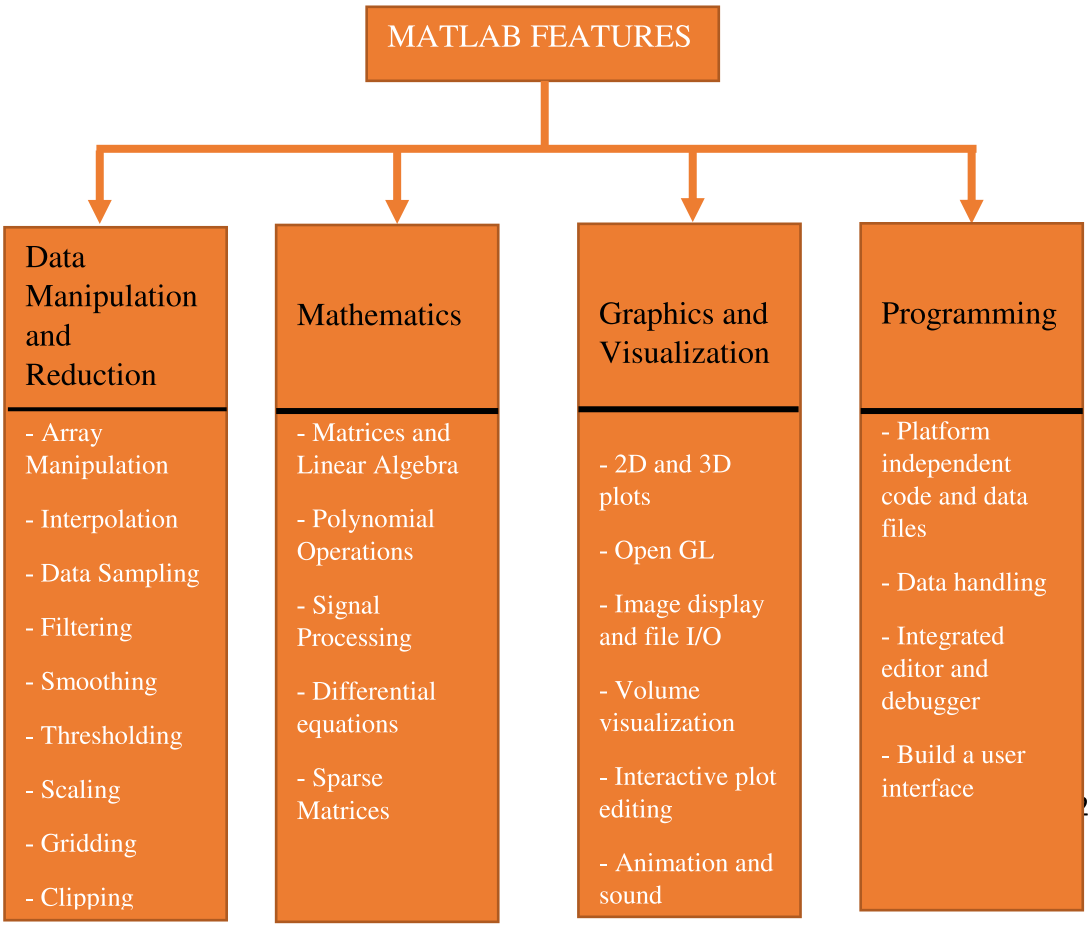


Fig. 4.1 showing MATLAB features

Image Processing Toolbox in MATLAB

MATLAB image processing tool helps in various works related to image that is non-perceivable by human as it is by equipment like digital detector, etc. The main tasks performed by MATLAB image processing tools are:

- Feature extraction
- Image Filtering
- Morphological operations
- Pixel-Based Processing
- Transformations on image
- Image compression
- Image Enhancement
- Image Segmentation and many more

Supported Image Formats

- BMP
- GIF
- JPEG
- HDF
- PCX
- PNG
- TIFF
- XWD
- PPM

Basic Functions Related to Images

- **To read an image**
  I=imread('path');
- **To write an image**
  imwrite (imagename,'path');
- **To display an image**
  Display;

Imshow(I);

- **To convert a RGB image into grayscale**

  J=rgb2gray(I);

- **To extract individual component of a RGB image**

  red_component=I(: : 1);

  green_component=I(: : 2);

  blue_component=I(: : 3);

- **To resize and crop image**

  X=imresize(imagename,scale);

  Z=imcrop(imagename);

4.2 DATASET USED

For the purpose of simulation of the proposed method, two datasets are used i.e. STructured Analysis of the Retina (STARE) [62] and Digital Retinal Images for Vessel Extraction (DRIVE) [61]. Both of the datasets are open source and free for download.

STARE dataset [62]

Acronym for STructured Analysis of the Retina, it is a project begun in 1975 by Michael Goldbaum, (Managing Director, University of California). Medical Fundus pictures and medical data was given by the Shiley Eye Center at the University of California and by the Veterans Administration Medical Center both located in San Diego.

Approx. 30 people volunteered for this project belonging to different backgrounds. This project basically focuses on automatic diagnosis of human eye disorder by scanning fundus image. This dataset contains approx. 400 RGB fundus images of PPM type of size 605*700 pixels.

DRIVE dataset [61]

Short for Digital Retinal Images for Vessel Extraction, the images for the DRIVE database were acquired from a diabetic retinopathy detection event in the Netherlands. It is an open source and free of charge dataset available for research work online. The event people involved 400 diabetic patients between 25-90 years of age. 40 images were randomly selected, among which 33 didn't indicate any symbol of diabetic retinopathy and seven among them indicate symbols of slight initial diabetic retinopathy. Each fundus photograph is of .tif extension.

The fundus photos were gotten by means of a Canon CR5 non-mydriatic 3CCD camera along a 45° field of view. Every image was taken by means of 8 bits per color plane with size 768*584 pixels.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

A better medical fundus image enhancement algorithm is proposed here. Fundus RGB image is initially divided into its individual R, G and B components and then distinct filters were applied along with CLAHE to de-noise and improve contrast of the fundus image. At last, components were merged together to form enhanced RGB fundus image. Efficacy of the proposed method is proved by various performance and quality parameters like PSNR, SSIM and CoC. Results showed that the results of the proposed model is quite impressive in terms of the performance parameters value and also surpass basic CLAHE in terms of performance parameters.

Further, the proposed algorithm may be modified for better results and can be applied to other colored medical images like PET scan, etc.

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