Detection of Dark Lesions from Coloured Retinal Image Using Curvelet Transform and Morphological Operation

K.Gayathri, D.Narmadha, K.Thilagavathi, K.Pavithra and M.Pradeepa

Abstract: Automatic extraction of dark lesions from retinal images can assist in early diagnosis and screening of a common disease such as Diabetic Retinopathy. A robust and computationally efficient approach for the localization of the different features and lesions in a fundus retinal image is presented in this paper. The proposed method consists of preprocessing, contrast enhancement, blood vessels extraction and dark lesions detection stages. In the preprocessing stage, since the green channel from the coloured retinal images has the highest contrast between the sub-bands, so the green component is selected. To uniform the brightness of an image adaptive histogram equalization are used. Furthermore Curvelet transform is used to enhance the contrast of the images by highlighting its edges in various scales and directions. The morphological function of Bothat and Tophat transformations followed by local thresholding is provided to classify blood vessels and dark lesions from the background. Eventually, by applying tophat transformation and wiener filter the dark lesions alone separated from the blood vessels.

Keywords: Bothat, Curvelet transform, morphological function, dark lesions, retina, Tophat.

I. INTRODUCTION

The most important internal components of eye is called retina, which covers all posterior compartment. Any damage in retina leads to severe diseases. Disorders in retina resulted from special diseases are diagnosed by special images which are obtained by using optic imaging called Fundus image. The Fundus images are used for diagnosis by trained clinicians to check for any abnormalities or any change in the retina. They are captured by using special devices called ophthalmoscopes. Each pixel in the fundus image consists of three values namely Red, Green and Blue, each value being quantized to 256 levels. The blood vessels are the important parts of the retinal images consisting of arteries and arterioles. Checking the obtained changes in retinal images can help the physician to diagnose the diseases.

K.Gayathri, D.Narmadha and K.Thilagavathi are with Department of ECE, the PG Students of M.E.Applied Electronics, C.Abdul Hakeem College of Engineering and Technology, Melvisharam.
(Email: kgayathri.be.ece@gmail.com; srinana1822@gmail.com; skthilaga03@gmail.com).
K.Pavithra is the student of Department of ECE, C.Abdul Hakeem College of Engineering and Technology, Melvisharam.
(Email: kpavithra.519@gmail.com)
M.Pradeepa is working as Associate Professor in Department of ECE, C.Abdul Hakeem College of Engineering and technology, Melvisharam. (Email: prathi_kavi@yahoo.co.in).

Applications of retinal images are diagnosing the progress of some cardiovascular diseases, diagnosing the region with no blood vessels (Macula), using such images in helping automatic laser surgery on eye, and using such images in biometric applications, etc. Diabetic retinopathy (DR) is damage to the retina caused by complications of diabetes mellitus, which can eventually lead to blindness. There may exist different kinds of abnormal lesions caused by diabetic retinopathy, the most frequent being dark lesions such as microaneurysms, hemorrhages and bright lesions such as hard and soft exudates.

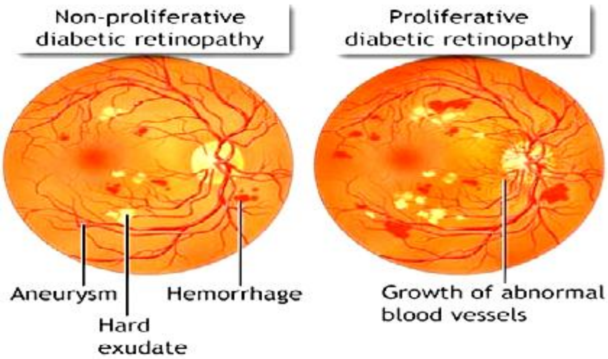

Fig.1. Retinal images with lesions

In modern years, about 80% of patients suffering from diabetes mellitus for over ten years have also suffered from diabetic retinopathy (DR). In fact, it is 4.8% of all the cases of blindness worldwide .The severity depends on the years that the specific patient has experienced the disease, and in worst case, can eventually lead to blindness. The early stage is further classified as mild NPDR (Non-Proliferative diabetic retinopathy) and moderate to severe NPDR. In mild NPDR, signs such as microaneurysms, dot and blot hemorrhages and hard or intraretinal exudates are seen in the retinal images. Microaneurysms are small, round and dark red dots with sharp margins and are often temporal to macula. Their size ranges from 20 to 200 microns i.e., less than 1/12th the diameter of an average optic disc and are first detectable signs of retinopathy. Proliferative diabetic retinopathy (PDR), which is defined as the growth of abnormal new vessels on the inner surface of the retina is divided into two categories: neovasculature of the optic disk and neovascularization elsewhere in the retina. PDR is the advance stage of DR, in which the retinal vessel may become blocked causing the retina to grow new vessels which is weak and prone to leakage. These new vessels may swell and becomes fluffy white patches called cotton wool spots. Moreover, blood from the vessels may leak into the vitreous, the gel in the center of the eyes. This is called vitreous hemorrhage. It can prevent the light to go through to the retina, and thus lead to bad vision. To most researchers, the lesions in the DR are classified into dark lesions which are also known as red lesions, consisting of hemorrhages and microaneurysms, and bright lesions, consisting of exudates and cotton wool spots. In the proposed method, the focus will be on the detection of dark (red) lesions which are very important as they represent the early sign of diabetic retinopathy (DR).

II. RELATED WORK

Recently many automated detection techniques are constantly devised and implemented to help ophthalmologists detect various diseases by applying image processing and pattern recognition techniques.

Acharya *et al.* [4] used morphological image processing to detect various lesions. First, an image with blood vessels was extracted by using 'ball' shaped structuring elements, in addition to morphological operations. Then, other image with the vessels as well as hemorrhages was extracted using the same technique but slightly increased the ball size. The final detection was obtained by subtracting the image with vessels alone from the image with vessels as well as hemorrhage.

A.M. Mendonça *et al.* [13] used mean filter to the original image, obtaining a normalized image and scaling as preprocessing techniques. To discriminate red lesions from blood vessels "top-hat" transform and a gaussian shaped matched filter is used. Abhir Bhalerao *et al*. [3] used median filter for contrast normalization and contrast enhancement as preprocessing techniques. Orientation matched filter was used to differentiate microaneurysms from blood vessels. Thresholding on the output of orientation matched filter is done to obtain a set of potential candidates (MAs). Eigen image analysis applied to the potential candidate regions and a second threshold applied on the Eigen-space projection of the candidate regions eliminated certain noise artifacts.

Iqbal, M.I *et al*. [8] used Color Space Conversion, Edge Zero Padding, Median Filtering and Adaptive Histogram Equalization as pre-processing techniques and they used segmentation to group the image into regions with same property or characteristics. Methods of image segmentation include simple thresholding, K-means Algorithm and Fuzzy C-means. R. Priya and P. Aruna [16] used pre-processing techniques like Gray scale Conversion, Adaptive Histogram Equalization, Matched Filter Response and proposed a method for feature extraction based on Area of on pixels, Mean and Standard Deviation. M. Kalaivani, M. S. Jeyalakshmi, V. Aparna [12] used Adaptive Histogram Equalization for initial enhancement, followed by this the curvelet transforms to the equalized image and the curvelet coefficients are obtained. The vessel extraction is done based on thresholding technique and the Kirsch's templates. It involves spatial filtering of the image using the templates in eight different orientations. The masking of redundant regions in the obtained output image is carried out using boundary techniques. A. Shaeidi [19] used Dynamic Thresholding to identify whether a pixel is MA or not based on color, size, shape and intensity features. In this paper, the abnormalities are detected by processing a retinal image using mathematical Morphological transformations.

The rest of the paper is organized as follows: Section 3 proposed method is described while section A &B examines green sub-band selection and image enhancement using adaptive histogram equalization, Section C describes Contrast enhancement using FDCT and section D&E presents the method for extraction of vessels and dark lesions from colored retinal image. In section 4 the results of the algorithm over an extensive dataset are presented.

III. PROPOSED METHOD

The proposed method in this work consists of following steps. The blood vessels extraction and dark lesions detection are shown in Fig.2.

A. Green sub-band selection

If the three channels of a colour fundus image are observed, the red channel shows a poorly contrasted retinal vasculature on top of the choroidal vasculature. The Green channel shows well contrasted arteries and veins with a clear dark fovea in the centre. The blue channel shows a noisier image of the vasculature. So the sub-band G (Green) is selected from the colored retinal images has the best contrast by experience.

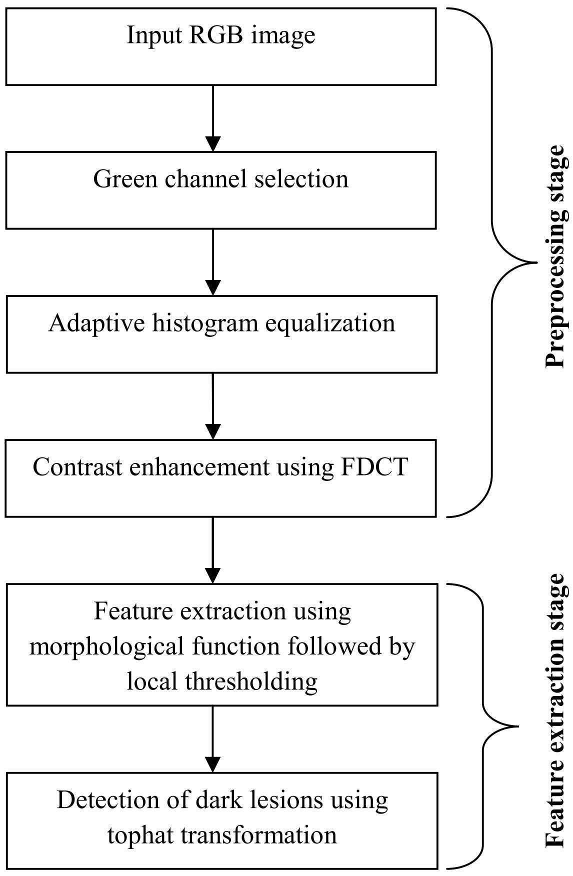

Fig.2. Block diagram of Dark Lesions Detection

B. Adaptive histogram equalization

We initially work on the color image contrast of original color image is increased so that blood vessels and dark lesions are highlighted. Adaptive Histogram

Equalization is an enhancement technique capable of improving images Local Contrast. It differs from ordinary histogram equalization in the respect that adaptive method computes several histograms each corresponding to distinct section of the image and uses them to redistribute the lightness values of image.

C. Contrast Enhancement using Fast Discrete Curvelet Transform

Curvelet transform is developed to overcome the limitation of wavelet and Gabor transforms [9]. Although, wavelets are widely used in feature extraction but it fails to handle randomly oriented edges of the object and the singularities of the object. Gabor filters overcome the limitation of wavelet transform and deal with the oriented edges, but it loses the spectral information of the image. Curvelet transform is used to overcome these problems of the wavelet and Gabor filters. It can obtain the complete spectral information of the image and handle with the different orientations of the image edges.

The idea of curvelet is to represent a curve as a superposition of functions of various lengths and widths obeying the scaling law width ≈ length^2. This can be done by first decomposing the image into sub-bands, i.e. separating the object into a series of disjoint scales. Then, each scale is analyzed by a local ridgelet transform. The newly constructed and improved version of the curvelet transform is known as Fast Discrete Curvelet Transform (FDCT). The new constructed version is faster, simpler and less redundant than the original curvelet transform, which based on Ridgelet. As mentioned, according to Cand'es *et al.* [6] two implementations of FDCT are proposed:

1. Unequally spaced Fast Fourier Transform (USFFT)
2. Wrapping Function

Both implementations of FDCT differ mainly in choosing the spatial grid that used to translate curvelet at each scale and angle. Both digital transformations return a table of digital curvelet coefficients indexed by scale, orientation and location parameters. Here, we use the wrapping method to implement the Fast Discrete Curvelet Transform (FDCT) on the retinal image which is a two-dimensional signal. The wrapping implementation is simpler, faster and has less computational complexity than existing approaches. Wrapping based curvelet transform is a multi-scale pyramid which consists of different orientations and positions at a low frequency level. Basically, multiresolution discrete curvelet transform in the spectral domain utilizes the advantages of fast Fourier Transform (FFT). During FFT, both the image and the curvelet at a given scale and orientation are transformed into the Fourier domain. At the end of this computation process, we obtain a set of curvelet coefficients by applying inverse FFT to the spectral product. This set contains curvelet coefficients in ascending order of the scales and orientations.

In order to obtain the curvelet coefficients for an image the above steps are performed sequentially.

1) Apply the 2D FFT and obtain Fourier samples

$$\hat{f}\ [n1,n2],\ -n/2<n1,\ n2<n/2 \qquad (1)$$

2) For each scale j and angle l, form the product

$$\tilde{U}_{j,l}[n1,n2]\ \hat{f}\ [n1,n2] \qquad (2)$$

Where, j, l [n1, n2] is the discrete localizing window.

3) Wrap this product around the origin and obtained

$$\hat{f}\ [n1,\ n2] = W(\tilde{U}_{j,l}\ \hat{f}\ )[n1,n2] \qquad (3)$$

Where, the range for n1 is now 0 < n1 < L1,j and 0 < n2 < L2 are constant.

4) Apply the inverse 2D FFT to each *f(j,l)*, hence collecting the discrete coefficients C^D (j, l, k).

Since the Curvelet transform is well adapted to represent the images containing edges, it is a good candidate for edge enhancement.

D. Extraction of blood vessels along with dark lesions

Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size [9].

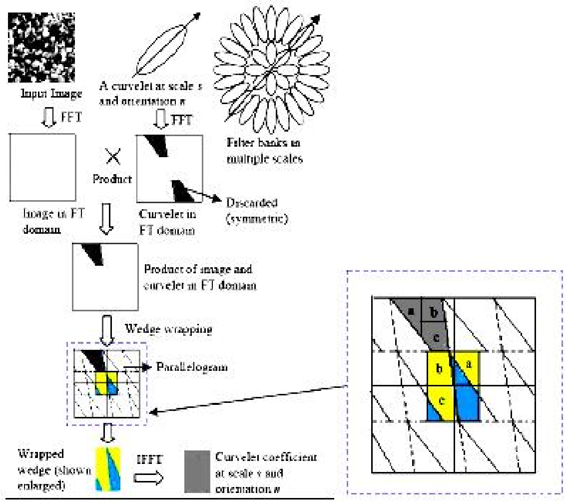

Fig.3. Steps in FDCT via wrapping method

In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. Many morphology functions are applied in feature extraction (e.g., opening), but the problem of this function is that the pixels in the resulted image can include all negligible changes in the grey levels existing in the image.

In our proposed algorithm, improved morphology function is used and it is defined as,

$$\textit{Improved function} = imsubtract\ \{(I_0 - (I_0 \circ SE) - (I_0 \bullet SE) - I_0)\} \qquad (4)$$

Where, I_0 is the image to be processed, ◦–opening operator, •–closing operator, SE is the disk shaped structuring element. A structuring element is a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. The pixels with values of 1 define the neighborhood. The center pixel of the structuring element, called the origin, identifies the pixel being processed.

The tophat transform is used for extracting small or narrow, bright or dark features in an image. It is represented as,

$$h = I_0 - (I_0 \circ SE) \quad (5)$$

The bothat transform, also called closing residue, is used to extract valleys such as dark lines and dark spots. It is a process which is done by the subtraction of the original image from the closing result. Therefore, the blood vessels of the retina, actually considered as dark lines are extracted by applying the bothat transform. The bottom-hat transform is expressed as the following equation,

$$h = (I_0 \bullet SE) - I_0 \quad (6)$$

In output of the improved function, an image is produced in which the edges are highlighted and so the sensitivity to the noise is resolved. There occur some frills in the final edge image in addition to the extracted blood vessels and dark (red) lesions area because of the intrinsic noise in the retinal images. Thereby applying local thresholding, the rest of frills will be removed and the images of blood vessels along with the dark lesions are extracted from the retinal image.

E. Detection of dark lesions

After this segmentation, the candidate dark lesions are extracted by separating circular, nonconnected dark lesions from the blood vessels. Morphological tophat transformation is applied for this purpose. The tophat transformation is based on morphologically opening an image using a linear structuring element. Ten rotated structuring elements are applied with a radial resolution of 15°. The structuring element length should be chosen such that it must be larger than the largest dark lesion present in the set. As a result larger connected blood vessels are eliminated only the dark lesion part is separated from the background image.

IV. RESULTS

The proposed method for the automatic detection of red lesions was evaluated on the DRIVE, diaretdb0 and diaretdb1 databases. The experiments were implemented using the MATLAB version 7.5 software. Some of the values are different for different images, as they were estimated from different orientations and background settings.

A. Green sub-band selection

When the RGB coloured retinal images are visualized, it contains more intrinsic noise due to various lightning conditions. The green channel has shown in Fig. 5.shows the best background contrast, whereas the red and blue channels show poor contrast and are noisier. Therefore, the green channel was selected for further work.

B. Adaptive histogram equalization

To reduce the effect of different lightning conditions and to uniform Illumination Adaptive histogram Equalization is used. It improves the brightness of an image. This method computes several histograms each corresponding to distinct section of the image and uses them to redistribute the lightness values of image. So that contrast of the image was adjusted to the limit 0 and 1 is shown in Fig.6.

Fig.4. Input RGB image

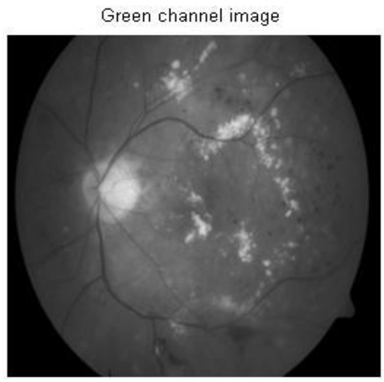

Fig.5. Green channel representation

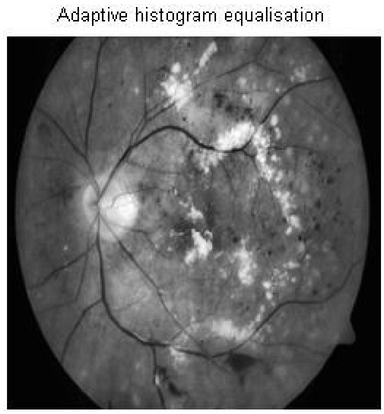

Fig.6. Adaptive histogram equalized image

C. Contrast Enhancement using Fast Discrete Curvelet transform

Further the contrast of the image is enhanced using FDCT via wrapping method. A set of scales, Sj and directional bands Di coefficients are obtained. For each directional band, C{1}{1} the minimum threshold value were determined and replaced all the coefficients with these values after that image was reconstructed using IFDCT(Inverse Fast Discrete Curvelet Transform) is shown in Fig.7.

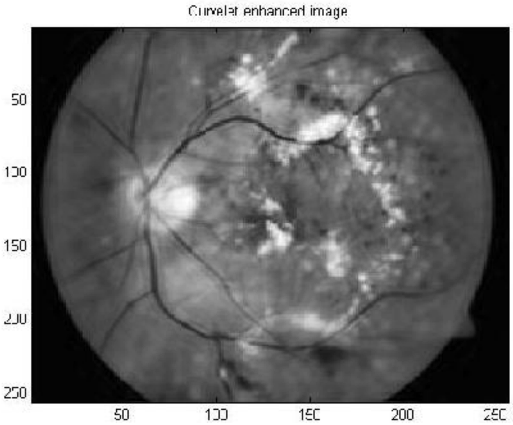

Fig.7. Curvelet enhanced image

D. Extraction of blood vessels along with dark lesions

A morphological operation was performed by highlighting the background to a disk size of 5. The highlighted background were subtracted using Tophat and Bothat transformation so the blood vessels along with dark lesions were shown much clearly when compared with the original image. The image was then converted to a binary image with local thresholding technique. The final image was displayed where the extracted region is shown in black and the background in white is shown in Fig.8.

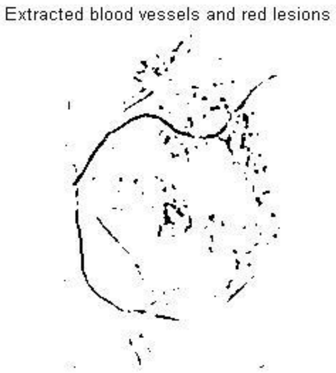

Fig.8. Segmented blood vessels with red lesions

E. Detection of dark lesions

Finally, the dark lesions alone are detected using morphological Tophat transformation with the aim of removing the large pixel blocks. Ten rotated structuring elements are applied with a radial resolution of 15°. The structuring element length should be chosen such that it must be larger than the largest dark lesion present in the set. As a result larger connected blood vessels are eliminated is shown in Fig.9. also by providing wiener filter only the dark lesion part is separated from the background image.

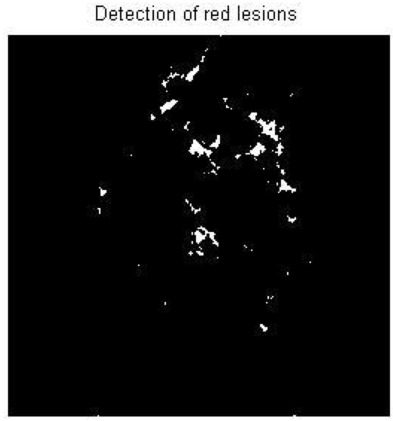

Fig.9. Dark lesions region

F. Evaluation parameters

To facilitate the performance of retinal lesions extraction algorithms, we have selected the PSNR and RMSE as performance measures. Those measures are estimated as follows.

Peak Signal to Noise Ratio (PSNR): PSNR evaluates the intensity changes of an image between the original and the processed image.

$$\text{PSNR} = 20 \log_{10} (255/\text{MSE})^2 \quad (7)$$

Mean Squared Error (MSE): MSE (Mean Squared Error) is computed via,

$$\text{MSE} = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \|I_0(i,j) - I_p(i,j)\| \quad (8)$$

$$\text{RMSE} = \sqrt{MSE} \quad (9)$$

Where, MSE are mean squared error of image, I_o is the original image, and I_e is the enhanced image.

TABLE I
PERFORMANCE ANALYSIS

Module	PSNR (dB)	RMSE
Enhancement Using FDCT	30.236	28.419
Extraction of Vessels along with dark(red) lesions using morphological operation	31.56	22.89
Detection of Dark lesions	34.48	22.67

V. CONCLUSION

Here we present a novel method for detection of dark (red) lesions. It has considered the criteria for assessing the methods used for enhancing the contrast of the images and extracting the blood vessels. Since the Edge enhancement plays an important role in the final extraction results, applying histogram equalization on retinal image will have a noticeable effect on both having the retinal images with uniform illumination as well as improving the accuracy of the final edge image. Considering the aforesaid attributes of the Curvelet transform, it was seen that, this developed instrument has served successful in enhancing the contrast of the images. In the method of combination of tophat and bothat morphology function with structuring elements followed by local thresholding, the structure elements act with more power in recognizing the edges. At last by applying tophat transformation and wiener filtering technique only the dark lesions region are separated from the background. It can be concluded that the algorithm is a proper success in fulfilling the goals.

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First K.Gayathri graduated her B.E. in Electronics and communication engineering from C.Abdul Hakeem College of Engineering and Technology, Melvisharam. She is currently pursuing the M.E. (Applied Electronics) from C.Abdul Hakeem College of Engineering and Technology, Melvisharam.

She has published many papers in National and International conference proceedings. She attended many workshops in SCARA Robots, Robotics and embedded system design. Her research interests include Image Processing, Embedded system Design, Pattern Recognition and Multiscale methods in image processing. She is an active member of IETE.

Second D.Narmadha received B.E(ECE) in Ranganathan Engineering College, Coimbatore. She is currently pursuing Master of Engineering in Applied Electronics, C.Abdul Hakeem College of Engineering and Technology Melvisharam.

She has presented many papers in National and International Conferences. She attended workshop in Implementational Aspects of Microcontrollers. Her Area of research includes ImageProcessing, Networking, Embedded System. She ia an active member of IETE.

Third K.Thilagavathi Started Career towards Engineering in 2011 as B.E(ECE) student. She is curretly doing Master of Engineering in Applied Electronics at C.Abdul Hakeem College of Engineering and Technology, Melvisharam.

She attended many workshop in Embedded System and VLSI domains. She has presented in many national and International conferences. Her Area of interest includes Image Processing, VLSI, Embedded System Design, Verilog, Networking. She ia an active member of IETE.

Fourth K.Pavithra is currently pursuing her B.E. (ECE) at C.Abdul Hakeem College of Engineering and Technology, Melvisharam. She has presented many papers in National Level Technical Symposium. She attended many workshops. Her area of interest includes Digital Image Processing, Digital Electronics, Microcontrollers and Electronic Circuit Designs.

Fifth M.Pradeepa graduated B.E. in Electronics and communication engineering from Bharadhidasan University in 2002 and received the M.E.(Computerr & Communication) from Anna university in 2004. She is currently pursuing the Ph.D. under the area of Signal Processing.

She is presently working as Associate Professor at Electronics and Communication Engineering, C.Abdul Hakeem College of Engineering and Technology, Melvisharam. She has published many research papers in International Journal and International Conferences. Her research interests include Signal Processing. She is an active lifetime Member of ISTE.