A Multidisciplinary Indexed International Research Journal

ISSN: 23203714 Volume : 5

ADHYAYAN INTERNATIONAL RESEARCH ORGANISATION

EXECUTION OF AN IMAGE PROCESSING MODEL FOR THE ANALYSIS OF DIABETIC NEPHROPATHY IMAGES

Shreesha Kalkoor M., Research Scholar, Sunrise University, Rajasthan

Under the Guidance of: Dr. Sachin Saxena, Supervisor, Sunrise University, Rajasthan

***Abstract*—Diabetic Nephropathy is the leading cause of chronic renal disease and a major cause of cardiovascular mortality. Diabetic Nephropathy has been categorized into stages: micro albuminuria and macro albuminuria. Nephropathy is pathologically characterized in individuals with type diabetes by thickening of glomerular and tubular basal membranes with progressive mesangial expansion (diffuse or nodular) leading to progressive reduction of glomerular filtration surface. It increases risk of death, mainly from cardiovascular causes and is defined by increased urinary albumin excretion (UAE) in the absence of other renal diseases.**

In this dissertation a new algorithm is proposed to analyse the underlying problems present in acquired images of Diabetic Nephropathy. Here pre-processing techniques like Contrast Enhancement, Image Enhancement, BIHE and CLAHE as well as post-processing techniques like Cell Detection, Watershed Segmentation and Image Segmentation are used. By combining these two techniques, an adaptive image processing model for the analysis of Diabetic Nephropathy images is designed which is used for development of the frame work. This model is useful for easy analysis of Diabetic Nephropathy images. This model is also useful as an educational tool for common man. In this research work the exploration or investigation of the significance of less commonly used estimate parameters in the process of medical image analysis is done.

***Keywords*— Contrast Enhancement, Image Enhancement, BIHE, CLAHE, Cell Detection, Watershed Segmentation and Image Segmentation**

I. INTRODUCTION

A. Edge Detection

Edge detection is a fundamental tool used in most image processing applications to obtain information from the frames as a precursor step to feature extraction and object segmentation. This process detects outlines of an object and boundaries between objects and the background in the image. An edge detection filter can also be used to improve the appearance of blurred image; to this cause more studies take this subject can be give some of these studies briefly: Soft computing techniques have found wide applications. One of the most important applications is edge detection for image segmentation. The process of partitioning a digital image into multiple regions or sets of pixels is called image segmentation. Edge is a boundary between two homogeneous regions. Edge detection refers to the process of identifying and locating sharp discontinuities in an image.

An Edge in an image is a significant local change in the image intensity, usually associated with a discontinuity in either the image intensity or the first derivative of the image intensity. Discontinuities in the image intensity can be either Step edge, where the image intensity abruptly changes from one value on one side of the discontinuity to a different value on the opposite side, or Line Edges, where the image intensity abruptly changes value but then returns to the starting value within some short distance.

Edge detection obtains the orientation directly from the kernel with the maximum response. This gradient based edge detector is estimated in the 3x3 neighbourhood for eight directions. All the eight convolution masks are calculated. One convolution mask is then selected, namely that with the largest module.

Edge detection is more common for detecting discontinuities in gray level than detecting isolated points and thin lines because isolated points and thin lines so not occur frequently in most practical images. The edge is the boundary between two regions with relatively distinct gray level properties. It is assumed here that the transition between two regions can be properties. It is assumed here that the transition between two regions can be determined on the basis of gray level discontinuities alone.

II. GRADIENT OPERATOR

The gradient of an image *f(x, y)* at location *(x, y)* is the vector:

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \partial f / \partial x \\ \partial f / \partial y \end{bmatrix} \quad \text{........... (1)}$$

The gradient vector maximum rate of change of *f*at *(x, y)*. In edge detection, an important quantity is the magnitude of this vector point's direction of in the:

$$|\nabla f| = \sqrt{G_x^2 + G_y^2} \quad \text{..................}$$

The gradient takes its maximum rate of increase of *f(x, y)* per unit distance in the direction of f.

The gradient magnitude is commonly approximated by:

$$|\nabla f| = |G_x| + |G_y| \quad \text{......................... (3)}$$

This is simpler to implement. The direction of the gradient vector is also important and is given by:

$$\alpha(x, y) = \tan^{-1}\left(\frac{G_y}{G_x}\right) \qquad \ldots\ldots\ldots\ldots (4)$$

III. EDGE DETECTION TECHNIQUE

A. *Laplacian Operator*

The Laplacian of an image *f(x, y)* is a second order derivative defined as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \qquad \ldots\ldots (5)$$

The digital implementation of the Laplacian function is usually made through the mask below:

0	−1	0
−1	4	−1
0	−1	0

Fig. 1 The Laplacian masks

The Laplacian is usually used to establish whether a pixel is on the dark or light side of an edge.

Fig. 2(a) Saturn Image

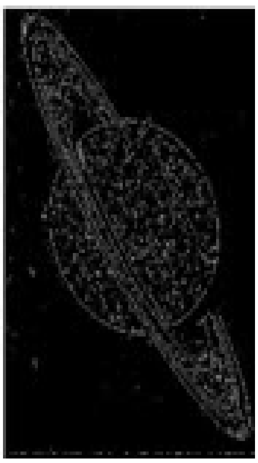

Fig. 2(b) Laplacian Image

The above images are the outputs of developed method, i.e., Contrast Adaptive Segmentation technique. We can conclude the reason for going to the new developed method as follows: The clear visual analysis for the output image after watershed segmentation is not present, hence the statistical values calculated are not considered. The edges are not perfectly detected, so the statistical parameters can show wrong results. Other existing methods Axon Segmentation and Texture image segmentation also tested, but they did not show up any results for the nephropathy images. The below are the statistical values of existing method (watershed Segmentation).

IV. RESULTS AND DISCUSSION

A. *Contrast Adaptive Segmentation*

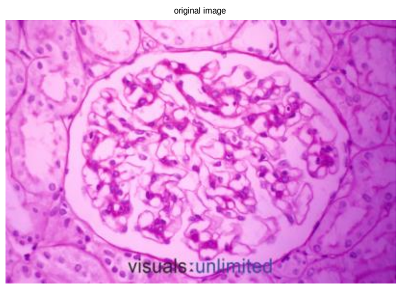

Fig. 3(a) Original Image showing the healthy condition of Base Membrane

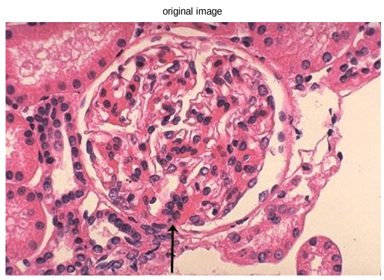

Fig. 3(b) Original Image showing mild expansion of Base Membrane

The above images are original Healthy and Disease affected electon microscopic images. In the first image by the visual inspection we can observe that the base membrane is not thick and the Macula Densa cells are not severe. In the fig. **3**(b), It is clear from the visual inspection that Basemembrane is slightly thickened and the macula densa cells (Black in color) are also densed.

Fig. 4(a) Grey scale converted image of figure 3(a)

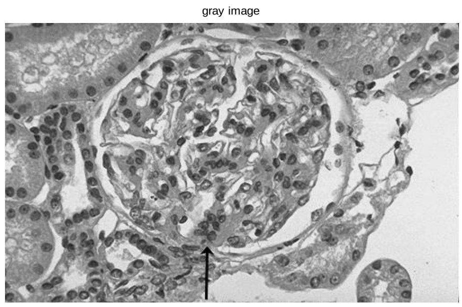

Fig. 4(b) Grey scale converted image of figure 3(b)

The above images are the grey scale converted images from the original color images of Fig. 3(a) and Fig. 3(b) respectively.

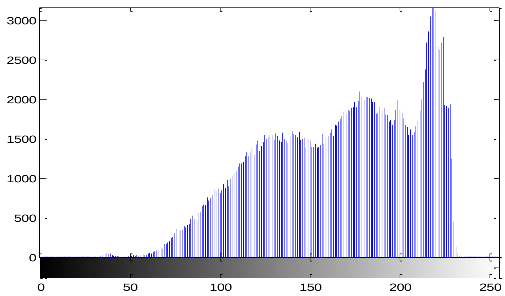

Fig. 5(a) Histogram of grey scale image in fig. 4(a)

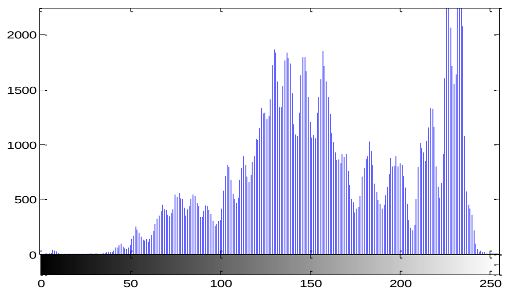

Fig. 5(b) Histogram of grey scale image in fig. 4(b)

The above images represent the histogram informations of Fig. 4(a) and Fig. 4(b) respectively.

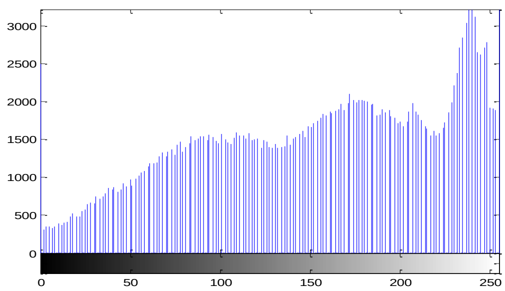

Fig. 6(a) Histogram of fig. 5(a)

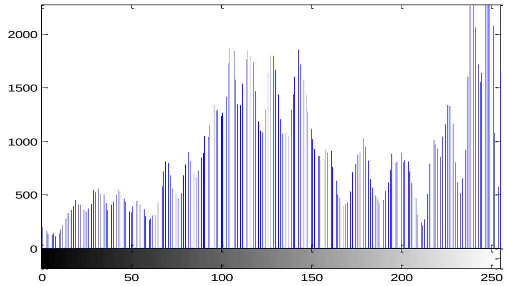

Fig. 6(b) Histogram of fig. 5(b)

The above images represent the histogram informations of Fig. **5**(a) and Fig. **5**(b) respectively.

Fig. 7(a) Image after subjecting fig. 4(a) to Contrast Limited Adaptive Histogram Equilisation (CLAHE)

Fig. 7(b) Image after subjecting fig. 4(b) to Contrast Limited Adaptive Histogram Equilisation (CLAHE)

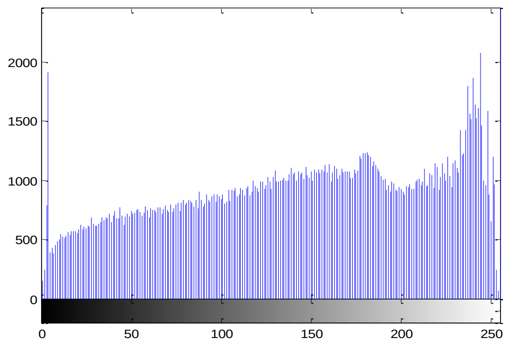

Fig. 8(a) Histogram of fig. 7(a)

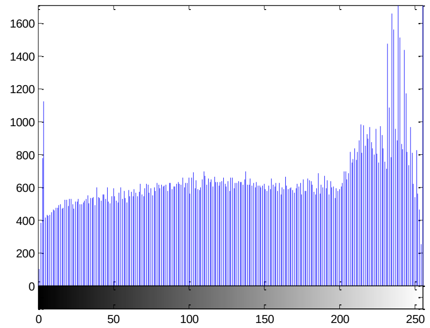

Fig. 8(b) Histogram of fig. 7(b)

The above images represent the histogram informations of Fig. 7(a) and Fig. 7(b) respectively.

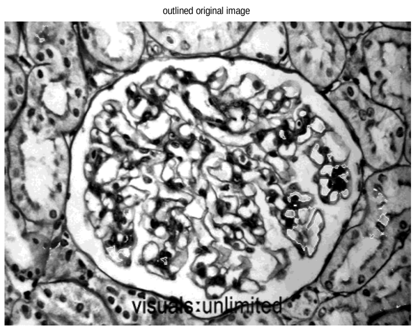

Fig. 9(a) Outlined original grey image

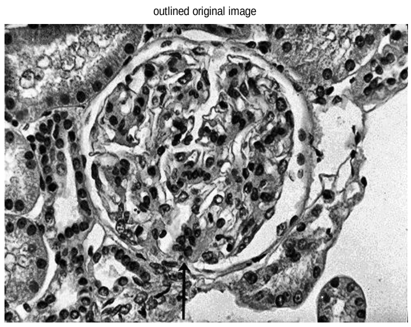

Fig. 9(b) Outlined original grey image

The above images are the outputs of developed method, i.e., Contrast Adaptive Segmentation technique. We can conclude the reason for going to the new developed method as follows:The clear visual analysis for the output image after watershed segmentation is not present, hence the statistical values calculated are not considered. The edges are not perfectly detected, so the statistical parameters can show wrong results. Other existing methods Axon Segmentation and Texture image segmentation also tested, but they did not show up any results for the nephropathy images. The below are the statistical values of existing method (watershed Segmentation).

B. Existing Technique Parameters

Parameters	Watershed Segmentation output
AREA	57245
PERIMETER	854
STD. DEVIATION	52.6
MEDAIN	146
SLICE DISTANCE	290
SUM OF INTENSITIES	8260801
CIRCULARITY	0.98

Table 1. Existing Technique Parameters

C. Statistical Analysis through Implemented Method

Parameters	Normal Condition		Abnormal Condition	
	Input Image	Output Image	Input Image	Output Image
AREA	362997	115616	58363	60895
PERIMETER	2476	1242	867	883
STD. DEVIATION	53.99	76.62	48.55	74.39
SKEWNESS	-0.491	-0.444	-0.069	-0.0876
MEDAIN	205	175	152	136
SLICE DISTANCE	898.13	444.85	292.26	298.73
SUM OF INTENSITIES	71688416	18120080	9108360	8123942
CIRCULARITY	0.744	0.947	0.973	0.979

Table 2. Contrast Adaptive Segmentation Parameters

Region Of Interest (ROI): Base Membrane intensity in the Glomerular Cell.

- Decrease in area indicates that ROI i.e., the degree of severity increases.
- Decrease in perimeter indicates that ROI i.e., the degree of severity increases
- Increase in the standard deviation indicates that ROI i.e., the intensity levels in the ROI

decreased as the Base Membrane got thickened.

- Decrease in slice distance indicates in that ROI i.e., the inter-pixel distance decreases, which indicates the increase in the severity.
- The variation in skewness (decrease or increase) gives the asymmetry of a distribution.
- Decrease in Median shows the Average changes of the pixels that occurred in the segmented image.
- Circularity in the ROI indicates that the similarity of the object to that of a circle. i.e., the circularity increases the severity increases.

According to the values obtained, on comparing the output images of normal and abnormal conditions, the decrease in the area indicates the reduction in intensity values in the ROI, which directly indicates an increase in the severity level. Perimeter is directly proportional to area. Increase in the standard deviation indicates the variation in the intensity levels, as the Std. Deviation is less for the abnormal image, it is clear that the Base membrane is thickened. Median of the image is inversely proportional to the severity in the image. Circularity is increased in the abnormal image, which means the glomerular cell is bulged and near to the circularity.

D. VISUAL ANALYSIS

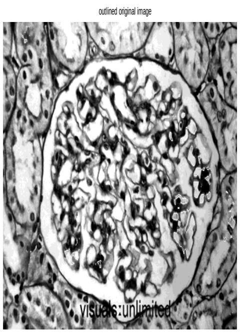

Fig. 10 Processed image showing the healthy condition of Base Membrane

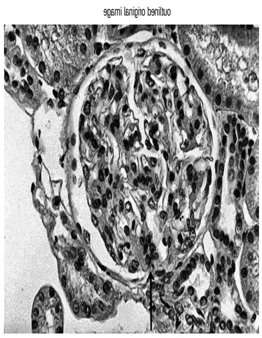

Fig. 11 Processed image showing mild expansion of Base Membrane**.**

From the visual perception, we can clearly say that the normal condition is having more spaces, and the affected cell having less spaces. The base membrane in the figure 11 is expanded which shows the intensity of the disease. As the visual and statistical results are far better than the existing method, the proposed method can be considered for achieving the goal.

V. CONCLUSIONS

Diabetes mellitus has become a worldwide epidemic, especially type 2 diabetes, which is expected to stand for decades to come. Diabetic nephropathy is the most frequent cause of terminal renal failure. So, once type 2 DM is diagnosed, patients should be screened for diabetic kidney disease on regular basis. These epidemiologic changes took place in parallel with marked changes in dietary habits and lifestyle that occurred in all Western and westernized populations which has shown its prevalence even on Asian Countries, characterized by a high calorie intake together with reduced physical activity.

REFERENCES

[1] A. C. Evans, D. L. Collins, and B. Milner. An MRI-based stereotactic atlas from 250 young normal.subjects. Society of Neuroscience Abstracts, 18:408, 1992.
[2] R C. Gonzalez and RE. Woods: Digital image Processing, Addison-Wesley Publishing Company, 1992.
[3] 1.C. Russ: The Image Processing Handbook (2101 edition), CRe Press, 2000.
[4] S.M.Pizer a al.: Adaptive histogram equalization and its variations, Coq>uter Vision, Graphics and Image Processing. Vol. 39, no. 3, pp 355-386.September 1987.
[5] V. Casells, J.L Lisani, J.M. Morel and G. Sapiro: Shape preserving local histogram modification, IEEE Trans. Image processing, vol. 8, 00. 2, pp. 220-230, 1998.
[6] 1.A. Stark: Adaptive contrast enhancement using generalization of histogram.equalization, IEEE Trans. Image processing, vol. 9, no. 5, pp. 889-906.2000.
[7] H. Huttunen and O. YLI-Harja: Fasl algorithm for updating the local histogram of mullidimensional signals, Proc. 1998 IEEE Internationalconference on Image Processing, 1998.
[8] OJ. Jobson, Z. Rahman and G.A Woodell: Properties and performance of a center/surround retinex, IEEE Trans. Image Processing,vol. 6, no. 3, pp. 451-462, 1997.
[9] S. Beucher. The Watershed Transformation Applied to Image Segmentation.Conference on Signal and Image Processing in Microscopy and Microanalysis, 16-19 September, 1991.
[10] A. Gavlasov´a, A. Proch´azka, and M. Mudrov´a. Wavelet Based Image Segmenatation. In Proc. of the 14th Annual Conference Technical Computing, Prague, 2006.