**I J C T A**, 9(3), 2016, pp. 1619-1631


# Automatic Diabetic Assessment System for Diabetic Retinopathy Using Image Analysis

**J. Vaishnavi*, S. Ravi** and M. Anousouya Devi, S. Punitha*****

***Abstract:*** Diabetic retinopathy is the leading disease that occurs due to the diabetic mellitus. Several computer aided diagnosis helps ophthalmologists to diagnosis the severity of retinopathy but still the annual screening of retinal images is very important to detect diabetic retinopathy by an automatic assessment system for analyzing the images through region based method, filtering techniques, template matching, thresholding and transformation methods. This paper provides a survey and analysis on an automatic diabetic assessment system for diabetic retinopathy using image analysis so that it can be used to screen the abnormalities like microanuerysms, exudates, hemorrhages, neovasculature in the non-proliferative and proliferative stages of diabetic retinopathy.

***Keywords:*** Region growing, thresholding, transformation, filtering, template matching.

## 1. INTRODUCTION

Diabetic milletus is the greatest social impact which is caused due to the imbalanced secretion of insulin in the blood. This leads to retinal abnormalities like micro aneurysms, new blood vessel growth, hard exudates, soft exudates, macular edema, hemorrhages etc. Several image processing techniques improves the detection and segmentation of retinal images to detection diabetic retinopathy. In the early stages, it is not an easy task for the ophthalmologists to screen the retinal images. Bad intensity, illumination, contrast, poor quality cameras, reflections were the major issues which holds the difficulties of the ophthalmologists. Diabetic retinopathy leads to total vision loss for the patients.

This is very important to screen the retinal images of the diabetic patients annually. Diabetic Retinopathy can be recognized as mild, moderate, non-proliferative and proliferative. The several stage of diabetic retinopathy is proliferative. Blood vessels are having computable changes in diameter, angles, branching etc.

There is a necessity for frequent classification and segmentation for the valuable treatment of the diseases. In the diagnosis of the fundus images of retina, some unwanted disturbances like background noises, illumination impairment. Preprocessing plays a vital role in reducing the background noises and filtering makes the images to have enhanced contrast. The automatic diabetic assessment system detects diabetic macular edema, fovea, blood vessels using region growing, thresholding, filtering and transformations methods has been detected. The region growing method performs well on segmenting the foreground from a noisy background image. In some cases, the seed pixel is placed which is time consuming for selecting the number of seed pixels and their locations. This is called seed based region growing and it causes over segmentation at vessel boundaries. The pattern recognition methods selects the varying size of patches which contains relevant and irrelevant patterns. Filtering and thresholding are used in the preprocessing stage so as to reduce the background noises.

* Research Scholar, Dept. of Computer Science, Pondicherry University, Pondicherry, *Email: roshugee@gmail.com*

** Asst. Professor, Dept. of Computer Science, Pondicherry University, Pondicherry, *Email: sravicite@gmail.com*

*** Research Scholars, Dept. of Computer Science, Pondicherry University, Pondicherry, *Email: anousouyadevi@gmail.com, punitharesearch@gmail.com*

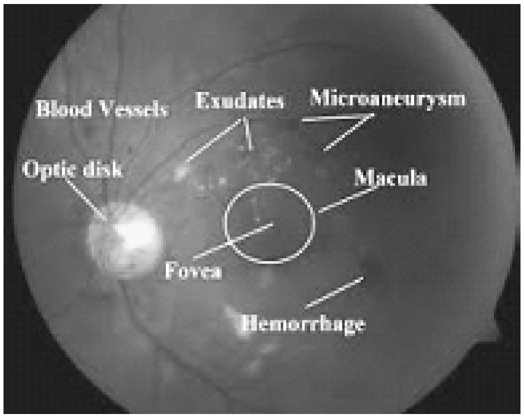


**Figure 1: Architecture of Expert system.**

Figure 1 shows the architecture of a retina image showing the different parts present in a retina like: Microanuerysms which is a first stage of diabetic retinopathy which is called mild non-proliferative diabetic retinopathy and it appears as dark lesions with thin capillary walls, Hemorrhages is leakage of thin weak capillaries with irregular margin and it is a moderate non-proliferative stage of diabetic retinopathy which leads to block the vessel tracks, hard exudates occurs in the outer layer of the retinal walls, which appears as the yellowish spots with sharp margins, Soft Exudates appears as white lesions similar to the optic disc which develops due to occlusion and Neovascularization an abnormal growth of blood vessels appears as loop and network. It is a proliferative stage of diabetic retinopathy.

The rest of the paper is organized as follows: section2 discusses the region based method for diabetic retinopathy, section 3 gives a detailed description about the Pattern recognition, section4 describes the watershed transformation, section 5 discusses filtering and thresholding techniques, section 6 gives a description about the paper with the survey table of various techniques Finally the paper is concluded in section 7.

## 2. AUTOMATIC DIABETIC ASSESSMENT SYSTEM FOR DIABETIC RETINOPATHY USING REGION BASED METHOD

The detection of diabetic retinopathy by an automatic assessment system for analyzing the images is done using region based method, filtering techniques, template matching, thresholding and transformation methods. Those methods are discussed one by one in the next section.

### 2.1. Region Based Method

Namita Sengar et al. [1] investigated the detection of diabetic macular edema in the images of retina using region based method. The detection of diabetic macular edema (DME) is done by dividing the retinal image in different regions as per the international standard. The 100 macular images for testing are collected from the database MESSIDOR and the detection is achieved with the accuracy of 80 to 90 % for different cases. The indirect method of detecting DME is detecting the hard exudates in the macular region. Morphological operator and dilation are used to detect the head exudates by removing unwanted brightest part.

### 2.2. Region Growing

M.H. Ahmad Fadzil et al. [2] observed the determination of fovea avascular zone (FAZ) in diabetic retinopathy digital fundus images. As a first step, detection and reconstruction of vessel and certain pathologies is done using median filtering and contrast is enhanced using CLAHE followed by bottom-hat transformation is used for background removal and contrast stretching. Vessels are extracted using seed based region growing and gradient based region growing. The accuracy ranges from 66.67 % to 98.69%. FAZ is not only used to detect the diabetic retinopathy but also to grade the severity of DR.

Jyoti Prakash Medhi et al. [3] proposed an automatic detection of Fovea using vessel free region. The proposed algorithm identifies the fovea region. The dark intensity property of fovea is utilized from the region of interest. The databases DRIVE, DIARETDB0, DIARETDB1, LOCAL, MESSIDOR achieves the detection accuracy of 100%, 96.85%, 97.67%, 98.46%, 96.25%, AND 100% respectively. The overall accuracy is 98.2%. If the intensity of the exudates are more than the optic disc, it will result in incorrect detection of the optic disc.

### 2.3. Post Filtration

Ahmed Wasif Reza et al. [4] proposed a quadtree based blood vessel detection algorithm using RGB components in fundus images which employs median filtering, quadtree decomposition, post filtering, postfilteration of detected edges and morphological reconstruction of retinal images. The quadtree provides information on different types of blocks and intensities of the pixel within the blocks. Post filteration and morphological reconstruction fills the edges of the blood vessels by removing the false alarms. DRIVE database is used and superimposition of three binary images are fed into quadtree decomposition is made. The true positive is 0.77.

## 3. AUTOMATIC DIABETIC ASSESSMENT SYSTEM FOR DIABETIC RETINOPATHY USING PATTERN RECOGNITION

### 3.1. Content based Image Retrieval

Gwénolé Quellec et al. [5] proposed a multiple instance learning framework for diabetic retinopathy screening to classify the images using patterns of arbitrary size. This work defines automatically the local reference score in the varying size of the patches. A content based image retrieval technique is used to search images in the large databases. A reference dataset is built and the image is divided into relevant and irrelevant. The local reference score increases if the patches contain relevant patterns. The MESSIDOR database is used.

### 3.2. Template Matching

Shan Ding and Wenyi Ma [6] proposed an accurate approach for microanuerysms (MA) detection in digital fundus images using a dynamic multi parameter template matching (DMPT) scheme. To extract the features of MAs an Adoptive weighted scoring algorithm is used. Dynamic template matching used sum of errors (SE) and correlation coefficients (CC) to measure the matching degree. The selected features are shape, pixel, algebra and other features to template matching process. By adding the adoptive weighted scoring and character based scoring (DCS-AWS), the greater sensitivity is achieved.

R. Geetha Ramani et al [7] proposed an automatic localization and segmentation of optic disc in retinal fundus images through image processing technique. Template matching and morphological procedures are used to localize and segment the optic disc region. A gold standard database from public repository is used which the accuracy of 98.7%. Cross correlation coefficient matrix is used to detect location of the optic disc. Ratio of cup and disc (CDR), ratio between optic rim and center of the optic disc are computed for the detection of the optic disc.

### 3.3. Vessel Pattern Segmentation

Annamaria Zaia et al [8] proposed the novel approach using an image processing approach for the detection of retinopathy with computer driven tracing of vessel network. In this work, thin capillary branches are identified by retinal vessel pattern segmentation. The proposed work is based on the shape modeling technique and local retinal vessel pattern methods and ocular backgrounds are tested. Two parameters used are: arteriovenous crossing (AVCA) and fractal dimensions (FC). Thresholding techniques also used for the segmentation along with shape modeling techniques.

### 3.4. Morphological Analysis

Carla Agurto et al [9] proposed a multiscale optimization approaches to detect exudates in the macula. To generate a candidate exudate region optimal thresholding of IA (Instantaneous amplitude) is extracted. The candidate features are color, shape and texture. Partial least square classification is used. Bottom up classification starts with the classification of individual pixels. A multiscale approach is used for combining the pixels to estimate the location of the DR lesions. The MESSIDOR database is used and its sensitivity is 100% and specificity is 73%.

Elaheh Imani et al [10] proposed the fully automated diabetic retinopathy screening using morphological component analysis to differentiate between normal and pathological retinal structure. As the first step, it removes the useless part of the images. In the second step, the quality of the images are evaluated using a novel algorithm. With the MESSIDOR database, it achieves 92.01% of sensitivity and 95.45% of specificity

Husna Ab Rahim et al [11] proposed methods to enhance digital fundus images for diabetic retinopathy detection. In this, three enhancement methods like histogram equalization (HE), Contrast limited adaptive histogram equalization (CLAHE) and Mahalanobis distance (MD) are used. Mahalanobis is the best for blood vessel image enhancement. DRIVE database is used.

Sayan Chakraborty et al [12] presented a semi-automatic system for optic nerve head segmentation in digital retinal images. Optic nerve head segmentation leads to the detection of many diseases like glaucoma and eye hypertension. It proposed a ground truth generation which converts RGB retina image to gray image using gamma correction, texture analysis, cropping and system obtained binary images and it manually defining independent contour. The independent contour used a drag able function which helps to move a point on the image so as to reduce the complexity of ophthalmologists to plot the point manually. A semi-automated system is more robust than a fully functional automated system.

### 3.5. Walter Klein Contrast Enhancement

Balint Antal et al [13] used an ensemble based system for microaneurysms detection and diabetic retinopathy which combines the preprocessing methods and candidate extractors. Walter Klein contrast enhancement is used in preprocessing to enhance the contrast of the images. CLAHE splits the images into disjoint regions and in each region a local histogram equalization is applied. Illumination equalization enhances the border of the retina.

## 4. WATERSHED TRANSFORMATION

### 4.1. Watershed with Hough transform

Thomas Walter et al [14] explained the contribution of image processing to the diagnosis of diabetic retinopathy. Morphological reconstruction techniques are used to find the exudates and contours. The optic disc is detected by watershed transformation. Images are analyzed by image enhancements, mass screening, monitoring of the disease. Images are enhanced by detecting noisy images, poorly contrasted images and non-uniform illuminated images. Automatic feature detection of the retina is used to identify the false positives of pathologies. Hough transform and watershed transformation is used to detect the optic disc contours and localization respectively.

### 4.2. Watershed Transform

Ahmed Wasif Reza et al [15] proposed the diagnosis of diabetic retinopathy by automatic extraction of optic disc and exudates from retinal images using marker controlled watershed transformation. This watershed transformation is made use of average filtering and contrast adjustments as preprocessing steps and the marker is used to modify the gradient before watershed transformation. The DRIVE and STARE database produces the sensitivity is 95%.

### 4.3. Watershed Algorithm with Splat Feature Segmentation

Arun G et al [16] proposed the detection of retinal hemorrhage in color fundus image using splat feature segmentation in which retinal image segments are called as splats. Splats are used to extract the appropriate boundary based on color, intensity and spatial location. Splats are irregular so it is easier to make it as group. Threshold value depends on the number of splats which are group of pixels with similar colours. Watershed algorithm is used for image segmentation with specific scale to clear boundaries to improve the accuracy. Removal of edge effects are made with splat standard reference to get maximum accuracy.

## 5. FILTERING TECHNIQUES AND THRESHOLDING

### 5.1. Gabor Filter with Local Entropy Thresholding

Saumitra Kumar Kuri [17] presented an automatic diabetic retinopathy detection technique using Gabor filter with local entropy thresholding. The color retinal images are acquired, then green channel extraction is done. The contrast of the image is enhanced by adaptive histogram equalization which divides the image into a number of tiles, in each tile histogram equalization is done. The texture is extracted by using Gabor filter and sinusoids modulated Gabor filter kernels are used to detect the blood vessels. Gabor filter is applied with local entropy thresholding for vessel extraction. The average accuracy and sensitivity is 97.72% and 98.15% respectively. The database used is DRIVE.

### 5.2. Edge Based and Strategic Thresholding Method

Malay Kishore Dutta et al [18] proposed a novel method for the detection of exudates in digital fundus image using edge based and strategic thresholding method which removes false detection of the noises. In pre-processing stage, colour normalization, contrast enhancement are made using tophat transform, the resultant image is converted into binary format and it is threshold based on the intensity level, the 97% intensity is set as threshold. Edges of the exudates are detected along with the edges of the blood vessels and microanuerysms. The two different methods detects different types of noises and the maximum noises are eliminated by the combination of strategic combination of two thresholding and edge detection methods.

### 5.3. Multi Scale Correlation Coefficient Filtering (MSCF) And Dynamic Thresholding

Bob Zhang et al [19] proposed a new method for the detection of microaneurysms using multi scale correlation coefficients in which new approach of computer aided diagnosis for diabetic retinopathy and the microanuerysms are detected using multi scale correlation coefficient filtering (MSCF) and dynamic thresholding. The two steps of detection are: microaneurysms candidate detection and microanuerysms classification. A coarse level detection is done to identify all microanuerysms. Multi scale Gaussian kernel method is used to calculate correlation coefficients. DIARETDB1 database is used foe effective and efficient classification.

Divyanjali Satyarthi et al [20] investigated an algorithm for the detection of diabetic retinopathy in fundus images using vector quantization technique in which the features are extracted in terms of the diameter of the blood vessels represented as ó and height of Gaussian profile across the cross section given by h. STARE database is used. The accuracy of the detection of neovascularization is 92%.

### 5.4. Adoptive Threshold

Shaunak Ganguly et al [21] observed an adoptive threshold based algorithm for detection of red lesions of diabetic retinopathy in a fundus image. The upper and lower thresholds of the retinal images are estimated for detecting the red lesions. Background shade correction is performed as a preprocessing stage. The sensitivity is 100% and the specificity is more than 99%. The Gaussian shaped cross section is used distinguish symmetrical vessel structures and asymmetrical blood vessels.

Subramaniam Ganesan et al [22] investigated an automated algorithm for retinal image exudates and drusens detection, segmentation and measurements in which the preprocessing is performed using image filtering, non-illumination and color contrast enhancement. The segmentation and classification is done using adoptive thresholding and morphological operators on DRIVE database. Median filter is used to remove noises. Color contrast enhancement is performed using the histogram equalization to identify the size if the exudates polyarea function is used.

Enrico Grisan et al [23] presented a novel technique for the segmentation of candidate dark lesions in fundus images based on local thresholding and density in which hemorrhagic dark lesions are identified by thresholding along with the spatial density of the pixel. Six images are selected in which the minimum area of the lesions are 26 pixels and the maximum was 7477 pixels. The lesions which appear as dark as the background shows the presence of dark lesions. The mean detection rate of 94% lesion in the image.

### 5.5. Active Shape Model

Huiqi Li et al. [24] proposed an automated feature extraction method in color retinal images using a model based approach. A modified active shape model is used in the detection of optic disc. The exudates are detected by combining region growing and edge detection methods. To detect the exudates three strategies are used like thresholding, edge detection and classification. Principle component analysis (PCA) is used to locate optic disc by obtaining the disc space and by calculating distance from the disc. The optic disk boundary is detected in order to find the progress of the eye disease and treatment results. The sensitivity and specificity of the exudate detection is 100% and 71% respectively.

### 5.6. Gabor transform

William Lasso et al. [25] proposed blood vessel segmentation in retinal images using convolutional filters, Gabor transform and skelitonization. Digital algorithms are very important for analyzing retinographies and is implemented by Fourier transforms, Gobor transforms of 2 dimension and convolution filters. Gabor function is used in texture segmentation and to detect the defects. This algorithm is based on time frequency and is powerful in digital image processing especially in enhancing filter edged and contours.

### 5.7. Multilayered thresholding

M. Usman Akram et al [26] observed the detection of neovascularization in retinal images using multivariate m-mediods based classifier in which the abnormal blood vessels are detected. The vascular pattern and optic disc are extracted by multilayered thresholding and Hough transform respectively. Binary masking and noise are eliminated in the preprocessing stage. Vessels are extracted using the features like structure, shape and size. The blood vessel segmentations are done using wavelet transformation. The databases used are DIARETDB and MESSIDOR.

Girish Singh Ramlugun et al [27] demonstrated a small retinal vessel extraction method towards proliferative diabetic retinopathy in which 2D match filters and CLAHE are used to enhance the retinal image vessel segmentation through double sided thresholding. Hysteresis thresholding is used for vessel reconstruction. The DRIVE database is used to extract vessels with the accuracy of 93.1%. The main drawback is that the threshold is to be set manually.

### 5.8. Dynamic Thresholding

Anantha Vidya Sagar et al [28] investigated a novel approach using dynamic thresholding and edge detection for automatic detection of exudates in digital Fundus retinal images. Optic disc is located by the principle component analysis (PCA). Active contour is used for the segmenting the boundary of the optic disc. Histogram and local contrast enhancement techniques are used in the preprocessing steps. Canny edge detector is used for detecting the exudates since the exudates are having sharp edges. The sensitivity is 99% and the mean predictivity is 93%. Ahmad Zikri Rozlan et al [29] proposed a diabetic retinopathy classification algorithm with statistical inference of exudates detection in which the rough and fine exudate detection is performed by column wise neighborhood operations and morphological reconstructions respectively. Local adoptive contrast enhancement is used to enhance the retinal background. Proper threshold determines the rough estimation of the exudates. To detect diabetic retinopathy, numerical index is computed using statistical analyzer software SPSS. M. Usman Akram et al [30] presented a novel method for the automated segmentation of blood vessels for detection of proliferative diabetic retinopathy in which the blood vessel segmentation is performed using the multilayered thresholding. Vascular patterns are enhanced using Gabor wavelets and adaptive thresholding is used to generate binary mask for blood vessel segmentation for detection for neovascularization. The abnormal vessels are detected using sliding window. The average accuracy of the proposed system is 0.9502.

### 5.9. Median filter

Priyakshi Bharali et al.[31] proposed an algorithm for the detection of hemorrhages in diabetic retinopathy analysis using color fundus image in which blood vessel is detected first then hemorrhage median candidate is detected and extracted. Median and average filter is used to reduce noise and CLAHE is used to enhance the contrast. The Databases used for the analysis are HRF, DIARETDB0, DIARETDB1, MESSIDOR gives the sensitivity of 97.3%, 98.92 %.

V. Krishna Sree et al [32] proposed a method for the diagnosis of Ophthalmologic Disordersin retinal fundus image. In the STARE database, the images are taken as input and the green component is extracted. Using Canny edge detector, edge strength is computed using the gradient of the images. Gaussian filtering is used to filter out any noise in the original image. In the second order filtering, adoptive histogram equalization is used for contrast enhancement. Finally median filter is used to reduce noises.

### 5.10. 2D Gaussian Match Filter

Aliaa Abdel-Haleim Abdel-Razik Youssif et al [33] investigated the optic disc detection from normalized digital fundus images by means of a vessels direction matched filter to detect the position of the Optic disc. Contrast equalization is done using adoptive histogram equalization methods. Retinal vessels are segmented using 2D Gaussian match filter. With the database STARE it achieves 98.77 % and with DRIVE database it gives 100% accuracy.

### 5.11. The Extended Median Filter

P. Subbuthai et al [34] proposed an algorithm for the restoration of retina images using extended median filter algorithm using the performance metrics such as peak signal to noise ratio, mean square error and root mean square error. This work proposes the extended median filter producing better results than the standard median filter in terms of noise suppression and detail preservation. DRIVE database is used. Image restoration is more efficient since the extended median filter uses not only a particular pixel but also the diagonal, vertical and horizontal elements.

Akara Sopharak et al [35] investigated an algorithm for the automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods. The non-dilated pupils reduces the examining time and the effect of the patient. Median filter and CLAHE is used for contrast enhancement. Optic disc can be easily identified as the largest area. Images are thresholded using the Otsu algorithms. Hard and soft exudates are detected using their color and sharpness of their borders.

### 5.12. Quadratic Isotrophic Filter

V. S. Hari et al [36] observed a quadratic filter for the enhancement of edges in retinal images for the efficient detection and localization of diabetic retinopathy. This work proposes a quadratic filters for detecting microanuerysms. Volterra filter is used for polynomial linearities. Teager filters are used to detect the edges of the retina. Quadratic isotrophic filter is used for optimization. STARE and HRF databases are used for testing. Quadratic filter is faster in detecting edge resolution and better than treager filter.

### 5.13. Minimum Cross Entropy Threshold

Saumitra Kumar Kuri et al. [37] proposed the automatic diabetic retinopathy detection using OMFR with minimum cross entropy threshold. An effective threshold technique is minimum cross entropy. RGB retinal image is used as an input for green channel extraction. Blood vessels are extracted using 2D optimized matched filter response. DRIVE database achieves accurate segmentation with the accuracy of 96.1% and sensitivity of 99.2%.

Arulmozhivarman Pachiyappan et al [38] investigated the automated diagnosis of diabetic retinopathy and glaucoma using fundus and OCT images. In this work, the macular abnormalities are detected using morphological procedures, filter and thresholds. Retinal nerve fiber layer (RNFL) is estimated for detecting the glaucoma. RFNL thickness is computed using active contour based deformable snake algorithm for segmentation. The final accuracy of the detection is 97.55%.

Marwan D. Saleh et al. [39] proposed an automated decision support system for non-proliferative diabetic retinopathy based on MAs and HAs detection in which the severity of the diabetic retinopathy is graded based on the location of the MAs and HAs. The dark spot segmentation like Mas and HAs are segmented using the h-maxima transformation for reducing the intensity levels, thresholding and feature extraction. The Kappa coefficients of the MAs and HAs are 68.98% and 74.91% respectively. The database of images are taken from university laboratory. This system achieves the sensitivity of 84.47% and specificity of 95.65% respectively.

Deepika Vallabha et al [40] proposed an automated detection and classification of vascular abnormalities in diabetic retinopathy. Selective Gabor filter bank is used to detect the abnormalities. Scale angle representation is used to identify the presence and absence of abnormalities. Canny's methods and gradient operators are used to detect the edges of the vessel. Minimum Mahalanobis is used as a classifier.

## 6. DISCUSSION

This paper provides the study and analysis on the methods used for the detection of diabetic retinopathy with the help of region growing, transformation methods, thresholding, morphological reconstructions, pattern matching and other techniques to find the abnormalities in the retinal fundus images and its performance measures in terms of accuracy, sensitivity and specificity with the publicly available databases like STARE, DRIVE, MESSIDOR and DIARETDB and also from some clinical laboratories.

Table 1 shows the analysis on the region based method used for the detection of diabetic retinopathy, where the macular edema and fovea can be easily found. Consideration of region of interest reduces the background noises by segmenting out the foreground images which needs to be diagnosed. This region growing technique allows for selecting out the nearest significant pixels with their locations while detecting the exudates and other abnormalities and also for classifying them as normal and abnormal. For testing the extraction and classification accuracy the databases used are DRIVE, MESSIDOR, DIARETDB1, DIARETDB0 etc. for achieving the maximum rate with less time consumption. Extracting the region of interest with the appropriate pixel values is the major issue.

Table 2 shows the analysis on the region based method used for the detection of diabetic retinopathy using the template matching, which is one of the best image classifier by segmenting relevant patterns and irrelevant patterns. The relevant patterns are to be selected with arbitrary size and pattern scoring enhances the detecting process more effectively. Template matching is used more in the detection of optic disc and lesions and in various medical automatic assessment systems. Templates can be resized accordingly.

Filtering and thresholding are the major part of detecting the abnormalities by reducing the background noises and by enhancing the contrast, eliminating poor quality features. Thresholding is works effectively in differentiating blobs, lesions with less time consumption. Edge sharpening, boundary correction are effectively done using filtering and thresholding. Table 3 shows the result analysis on the methods used for the detection of diabetic retinopathy.

**Table 1**
**The Result Analysis on The Region Based Method Used for The Detection of Diabetic Retinopathy**

| *Author* | *Method* | *Detected abnormality* | *Advantage* | *Disadvantage* | *Performance measure* | *Database* |
|---|---|---|---|---|---|---|
| Namita Sengar et al.[1] | Region based method | Macular edema | Severity detection and independency from optic disc detection | Classification of hard exudates and reflection has not been performed | Accuracy 80 to 90% | MESSIDOR |
| M.H. Ahmad Fadzil et al[2] | Region growing | Fovea avascular Zone | Severity grading | Tested with the smaller dataset | Accuracy in between 66.67 % to 98.69% | Clinical laboratory |
| Jyoti Prakash Medhi et al.[3] | Region of Interest | Fovea | Does not require spatial relationship of the optic disc location | Fovea alone has been detected. Must be checked with other abno-rmalities. | Efficiency of 98.21% | DRIVE, DIARETDB0, DIARETDB1, LOCAL, MESSIDOR |
| Ahmed Wasif Reza et al [4] | Post filteration and morphological reconstruction | Blood vessels | Time consuming | Appropriate block must meet some criteria | True positive 0.77 | DRIVE |

**Table 2**
**The Result Analysis on The Detection of Diabetic Retinopathy using The Pattern Matching**

| *Author* | *Method* | *Detected abnormality* | *Advantage* | *Disadvantage* | *Performance measure* | *Database* |
|---|---|---|---|---|---|---|
| Gwénolé Quellec et al[5] | Pattern recognition | Lesions | Can be applied to a various medical applications | More patterns are to be trained | – | MESSIDOR |
| Shan Ding and Wenyi Ma[6] | Multi parameter template matching | Micro aneurysms | Used multi-para-meter template and adopts double restraining factor | Severity grading has not been performed | Sensitivity with thresholds of two templates 0.4 & 0.5 | Clinical laboratory |
| R. Geetha Ramani et al.[7] | Template matching | Optic disc | Gives better accuracy | Can be tested with large databases | Accuracy of 98.7% | Gold standard database |
| Annamaria Zaia et al.[8] | Vessel pattern segmentation | Vessels | Various paramet-ers are combined to produce high quality | Specialization of shape modelling technique has not been used | Image fusion tech-niques has to be done | Geriatric Hospital |
| Carla Agurto et al.[9] | Optimal thres-holding | Exudates | Robust and does not require any retraining for the dataset. | No sight threaten-ing conditions due to the presence of exudates in the macula are missed | AUC 0.96 (with the combination of databases) | MESSIDOR |
| Elaheh Imani [10] | Morphological Component Analysis | Retinal Lesions | Performance based on textural features is greater. | Global transforms can be replaced by learned dictionaries to classify vessels and lesions | Sensitivity 92.01% Specificity 95.45% | MESSIDOR |

*(contd...)*

*(Table 2 contd...)*

| *Author* | *Method* | *Detected abnormality* | *Advantage* | *Disadvantage* | *Performance measure* | *Database* |
|---|---|---|---|---|---|---|
| Husna Ab Rahim et al.[11] | Mahalanobis Distance | Blood vessels | Achieves similar curves as Gaussian Curve. | Enhancement of MD creates fewer artefacts when further processing. | With varying luminosity and contrast testing has to been done | DRIVE |
| Sayan Chakraborty et al.[12] | Contour analysis | Optical nerve head | Reduces the limitations of fully automated system since there is also manual observations of the experts. | Examined with only limited datasets. | – | DRIONS |
| Bálint Antal et al.[13] | Ensemble based system | Lesions | Easily Extendible System with components | Misclassification is possible in some cases. | Sensitivity 90% Specificity 91% Accuracy 90% | MESSIDOR |

**Table 3**
**The Result Analysis on The Template Matching and Filtering Techniques used for The Detection of Diabetic Retinopathy**

| *Author* | *Method* | *Detected abnormality* | *Advantage* | *Disadvantage* | *Performance measure* | *Database* |
|---|---|---|---|---|---|---|
| Saumitra Kumar Kuri et al.[17] | Local entropy thresholding | Blood vessels | Can be used for image registration | Can improve the accuracy using various methods | Accuracy 97.72% Sensitivity 98.15% | DRIVE |
| Malay Kishore Dutta et al. [18] | Edge based and strategic thresholding method | Exudates | Reduces different types of noises and superior to single intensity thresholding | Classification of images has not been performed | – | – |
| Bob Zhang et al.[19] | Dynamic thresholding | Microaneurysm | Selection of scales and its combination improves the result. | Scale selection scheme is not automatic | Average of false positive 0.713 | ROC DIARETDB1 |
| Divyanjali Satyarthi[20] | Vector Qunatization | Blood vessels | Implementation of codebook | Size of the codebook is arbitrary | Performance 90% | STARE |
| Shaunak Ganguly et al.[21] | Adaptive threshold based algorithm | Red lesions | Adaptive and images are treated independently | Vessel detection is not concentrated | Sensitivity 100% Specificity 99% | - |
| Subramaniam Ganesan et al.[22] | Adaptive thresholding | Drusens | Also used to determine the severity | No special technique for removing optic disc | – | DRIVE |
| Enrico Grisan et al.[23] | Local thresholding | Dark lesions | Used as first stage of lesion detector system | No Multi level approach | Mean detection rate 94% | – |
| Huiqi Li et al. [24] | Active shape Model | Optic disc | Combination of two methods increases performance | Can be tested with huge database | Sensitivity in presence of exudates 100% | – |
| Akara Sopharak et al[25] | Morphological operators | Exudates | Fast and low computing power | Detection system can be improved for MA and HA | Average specificity 99.46% | – |
| M. Usman Akram et al[26] | Multilayered thresholding and hough transform | Blood vessels | Overlapping nature of distribution of samples | Totoursity has not been included | Accuracy 97.75% in diaretdb 98.24% in Messidor | DIARETDB MESSIDOR |
| Girish Singh | Hystersis | Vessels | Does not required | Thresholds has to | Better average | DRIVE |

*(contd...)*

*(Table 3 contd...)*

| *Author* | *Method* | *Detected abnormality* | *Advantage* | *Disadvantage* | *Performance measure* | *Database* |
|---|---|---|---|---|---|---|
| Ramlugun et al. [27] | thresholding | | a supervised method | be set manually | accuracy 93.1% | |
| Anantha Vidya Sagar et al.[28] | Dynamic thresholding | Exudates | Robust and reliable | Prediction of DR has not been performed with the changes | Sensitivity 99% predictivity 93% | – |
| M. Usman Akram et al.[30] | Multilayered thresholding technique | Blood vessels | Eliminates all false edges | – | Accuracy 96% | DRIVESTARE |
| Priyakshi Bharali[31] | NICK's local thresholding | Blood vessel | Gives good detection even with abnormalities | Severity of the abnormalities has not been computed | Sensitivity 97.3% Specificity 98.92% | HRFDIARETDB, MESSIDOR |
| V. Krishna Sree et al.[32] | Median filter | Optic disc | Robust and faster along with age related degeneration | Severity grading has not been done | Accuracy 78.9% | STARE |
| Aliaa Abdel-Haleim Abdel-Razik Youssif et al.[33] | 2D Guassian Matched Filter | Vessels | 2D vessel segmentation increases performance | Post processing can improve the performance | Detection rate 98.77% | STARE |
| P. Subbuthai[34] | Extended Median Filter | – | Eliminates bad quality features | Abnormality detection is absent | – | DRIVE |
| Akara Sopharak et al.[35] | Morphological | Exudates | Provides distance between exudates and macular | Problem in separating pathologies and small vessels | Sensitivity 80% Specificity 99.5% | – |
| V. S. Hari[36] | Isotropic quadratic Filter | Micro aneurysms | Better edge resolution | Tested with limited samples | – | STARE HRF |
| Saumitra Kumar Kuri et al.[37] | Minimum cross entropy threshold | Vessels | Distinguishes true vessel from non-vessel structures | Classifications of image has not been performed | Accuracy 96.1% Sensitivity 99.2% | DRIVE |
| Arunmozhivarman et al.[38] | Active contour Based | Glaucoma | Accepts both OCT and Fundus Images | Not available for rural areas | Accuracy 97.75% | – |
| Marwan D. Saleh et al.[39] | Thresholding and h-maxima transformation | Microanuerysms Hemorrhages | Post processing is done for improving the quality | Tested with only low quality images | Sensitivity 84.47% Specificity95.65% | University Laboratory |

**TABLE 4**
**The Result Analysis on The Watershed Transformations Techniques used for The Detection of Diabetic Retinopathy**

| *Author* | *Method* | *Detected abnormality* | *Advantage* | *Disadvantage* | *Performance measure* | *Database* |
|---|---|---|---|---|---|---|
| Thomas Walter et al.[14] | Watershed Transformation | Exudates | Robust with the changes of parameters | Tested with the smaller databases. Significance of soft and hard exudates are not possible. | Mean sensitivity 92.8%. Mean predictive value 92.4% | – |
| Ahmed Wasif Reza et al.[15] | Marker controlled watershed transformation | Optic disc | Can distinguish between lesions | Difference between normal and pathological retinas has not been included | Average sensitivity 95% | STARE DRIVE |
| Arun G et al.[16] | Watershed algorithm for segmentation | Hemorrhages | Occurrence of error is less | Splat limitation. If no. of splat increases originality is missed. | – | – |

In Table 4 the result analysis on watershed transformation technique used for the detection of diabetic retinopathy for detecting exudates, optic disc and hemorrhages and it is very effective in regulating the intensity values in their color spaces which makes to distinguish the features of the lesions. But it has to been tested with the larger databases.

## 7. CONCLUSION

This paper has presented the survey and analysis on automatic diabetic assessment system for diabetic retinopathy using image analysis through several methods like thresholding, transformation, pattern recognition, Filtration etc. This automatic assessment system of image analysis reduces the complexities of the ophthalmologist to screen the impairment of vision loss at an early stages. The detection rates of the abnormalities are tested through various databases like DIARETDB, MESSIDOR, DRIVE, STARE and DRIONS.

## *References*


[1] Sengar, N., Dutta, M. K., Burget, R., & Povoda, L. (2015). Detection of Diabetic Macular Edema in Retinal Images Using a Region Based Method, 412–415.

[2] Fadzil, M. H. A., Iznita, L., & Adi, H. (2010). Determination of foveal avascular zone in diabetic retinopathy digital fundus images. Computers in Biology and Medicine, 40(7), 657–664. http://doi.org/10.1016/j.compbiomed.2010.05.004

[3] Medhi, J. P. (n.d.). Automatic Detection of Fovea Using Property of Vessel Free Region.

[4] Reza, A. W., Eswaran, C., & Hati, S. (2008). Diabetic Retinopathy/ : A Quadtree Based Blood Vessel Detection Algorithm Using RGB Components in Fundus Images, 147–155. http://doi.org/10.1007/s10916-007-9117-5

[5] Quellec, G., Lamard, M., Abràmoff, M. D., Decencière, E., Lay, B., Erginay, A., … Cazuguel, G. (2012). A multiple-instance learning framework for diabetic retinopathy screening, 16, 1228–1240. http://doi.org/10.1016/j.media.2012.06.003

[6] Ding, S., & Ma, W. (2014). An Accurate Approach for Microaneurysm Detection in Digital Fundus Images, 1846–1851. http://doi.org/10.1109/ICPR.2014.323

[7] Geetharamani, R., & Dhanapackiam, C. (2014). Automatic Localization and Segmentation of Optic Disc in Retinal Fundus Images through Image Processing Techniques.

[8] Zaia, A., Maponi, P., Marinelli, M., Piantanelli, A., Giansanti, R., & Murri, R. (n.d.). Image Processing and Retinopathy/ : A Novel Approach to Computer Driven Tracing of Vessel Network, 575–584.

[9] Agurto, C., Murray, V., Member, S., Yu, H., Wigdahl, J., Pattichis, M., Soliz, P. (2014). A Multiscale Optimization Approach to Detect Exudates in the Macula, 18(4), 1328–1336.

[10] Imani, E., Pourreza, H., & Banaee, T. (2015). Computerized Medical Imaging and Graphics Fully automated diabetic retinopathy screening using morphological component analysis. Computerized Medical Imaging and Graphics, 43, 78–88. http://doi.org/10.1016/j.compmedimag.2015.03.004

[11] Rahim, H. A., Ibrahim, A. S., Zaki, W. M. D. W., & Hussain, A. (2014). Methods to Enhance Digital Fundus Image for Diabetic Retinopathy Detection, (Md), 7–9.

[12] Chakraborty, S., Mukherjee, A., Chatterjee, D., Maji, P., Acharjee, S., & Dey, N. (2014). Segmentation in Digital Retinal Images, (2004). http://doi.org/10.1109/ICIT.2014.51

[13] Balint Antal, Andras Hajdu, (2012a). An Ensemble-Based System for Microaneurysm Detection and Diabetic Retinopathy Grading, 59(6), 1720–1726.

[14] Walter, T., Klein, J.C., Massin, P., & Erginay, A. (2002). A contribution of image processing to the diagnosis of diabetic retinopathy-detection of exudates in color fundus images of the human retina. IEEE Transactions on Medical Imaging, 21(10), 1236–1243. http://doi.org/10.1109/TMI.2002.806290

[15] Reza, A. W., Eswaran, C., & Dimyati, K. (2011). Diagnosis of Diabetic Retinopathy/ : Automatic Extraction of Optic Disc and Exudates from Retinal Images using Marker-controlled Watershed Transformation, 1491–1501. http://doi.org/10.1007/s10916-009-9426-y

[16] Technology, A. C. A. D., Barriga, E., Murillo, S., Pattichis, M., Davis, H., Russell, S., & Abràmoff, M. (2015). Detection of Retinal Hemorrhage in Color Fundus Image using Splat Feature Segmentation.

[17] Kuri, S. K. (2015a). Automatic Diabetic Retinopathy Detection Using Gabor Filter with Local Entropy Thresholding.

[18] Malay kishore Dutta, M. K., Srivastava, K., Ganguly, S., & Ganguly, S. (2015). Exudates Detection in Digital Fundus Image Using Edge based Method and Strategic Thresholding, 748–752.

[19] Zhang, B., Wu, X., You, J., Li, Q., & Karray, F. (2010). Detection of microaneurysms using multi-scale correlation coefficients. Pattern Recognition, 43(6), 2237–2248. http://doi.org/10.1016/j.patcog.2009.12.017

[20] Satyarthi, D., Raju, B. A. N., & Dandapat, S. (2006). Detection Diabetic Retinopathy Images using Vector Quantization of, 7–10.

[21] Ganguly, S., & Ganguly, S. (2014). An Adaptive Threshold Based Algorithm for Detection of Red Lesions of Diabetic Retinopathy in a Fundus Image, 91–94.

[22] Ganesan, S. (2014). Automated Algorithm for Retinal Image Exudates and Drusens Detection, Segmentation, and Measurement, 206–215.

[23] Internationale, C., Grisan, E., & Ruggeri, A. (2007). Segmentation of candidate dark lesions in fundus images based on local thresholding and pixel density, 6735–6738.

[24] Li, H., Chutatape, O., & Member, S. (2004). Automated Feature Extraction in Color Retinal Images by a Model Based Approach, 51(2), 246–254.

[25] Lasso, W., Popular, U., Popular, U., & Torres, C. (1946). Image segmentation blood vessel of retinal using conventional filters, Gabor transform and skeletonization, (1).

[26] Akram, M. U., Khalid, S., Tariq, A., & Javed, M. Y. (2013). Computerized Medical Imaging and Graphics Detection of neovascularization in retinal images using multivariate m -Mediods based classifier. Computerized Medical Imaging and Graphics, 37(5-6), 346–357. http://doi.org/10.1016/j.compmedimag.2013.06.008

[27] Singh, G., Krishna, V., & Chakraborty, C. (2012). Expert Systems with Applications Small retinal vessels extraction towards proliferative diabetic retinopathy.

[28] Sagar, A. V., Balasubramaniam, S., & Chandrasekaran, V. (2007). A Novel Integrated Approach using Dynamic Thresholding and Edge Detection (IDTED) for Automatic Detection of Exudates in Digital Fundus Retinal Images, 0–5.

[29] Rozlan, A. Z., Hashim, H., Farid, S., & Hong, C. A. (2013). A Proposed Diabetic Retinopathy Classification Algorithm with Statistical Inference of Exudates Detection, 90–95.

[30] Akram, M. U., Jamal, I., Tariq, A., Imtiaz, J., & Introduction, I. (2012a). Automated Segmentation of Blood Vessels for Detection of Proliferative Diabetic Retinopathy, 25(Bhi), 232–235.

[31] Bharali, P., Medhi, J. P., & Nirmala, S. R. (2015). Detection of Hemorrhages in Diabetic Retinopathy analysis using Color Fundus Images, 237–242.

[32] Sree, V. K. (2014). Diagnosis Of Ophthalmologic Disordersin retinal fundus images, 131–136.

[33] Youssif, A. A. A., Ghalwash, A. Z., Ahmed, A., & Ghoneim, S. A. (2008). Optic Disc Detection From Normalized Digital Fundus Images by Means of a Vessels ' Direction Matched Filter, 27(1), 11–18.

[34] Subbuthai P., Muruganand S. ((2015), Restoration of retina images using Median Filter Algorithm.), 131–138.

[35] Sopharak, A., Uyyanonvara, B., Barman, S., & Williamson, T. H. (2008). Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods, 32, 720–727. http://doi.org/10.1016/j.compmedimag.2008.08.009

[36] Jagathy, V. S. H. V. P., & Gopikakumari, R. R. (2015). Quadratic filter for the enhancement of edges in retinal images for the efficient detection and localization of diabetic retinopathy. Pattern Analysis and Applications. http://doi.org/10.1007/s10044-015-0480-4.

[37] Saumitra Kumar Kuri (2015). Automatic Diabetic Retinopathy Detection Using OMFR with Minimum Cross Entropy Threshold, (May), 21–23.

[38] Pachiyappan, A., Das, U. N., Murthy, T. V. S. P., & Tatavarti, R. (2012). Automated diagnosis of diabetic retinopathy and glaucoma using fundus and OCT images, 1–10.

[39] Saleh, M. D., & Eswaran, C. (2012). An automated decision-support system for non-proliferative diabetic retinopathy disease based on MAs and HAs detection. Computer Methods and Programs in Biomedicine, 108(1), 186–196. http://doi.org/10.1016/j.cmpb.2012.03.004

[40] Vallabha, D., Dorairaj, R., Namuduri, K., & Thompson, H. (2004). Automated Detection and Classi fi cation of Vascular Abnormalities in Diabetic Retinopathy, 1625–1629.