# Histogram-Based Thresholding for Detection and Quantification of Hemorrhages in Retinal Images

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## Abstract:

Retinal image analysis is commonly used for the detection and quantification of retinal diabetic retinopathy. In retinal images, dark lesions including hemorrhages and microaneurysms are the earliest warnings of vision loss. In this paper, new algorithm for extraction and quantification of hemorrhages in fundus images is presented. Hemorrhage candidates are extracted in a preliminary step as a coarse segmentation followed by a fine segmentation step. Local variation processes are applied in the coarse segmentation step to determine boundaries of all candidates with distinct edges. Fine segmentation processes are based on histogram thresholding to extract real hemorrhages from the segmented candidates locally. The proposed method was trained and tested using an image dataset of 153 manually labeled retinal images. At the pixel level, the proposed method could identify abnormal retinal images with 90.7% sensitivity and 85.1% predictive value. Due to its distinctive performance measurements, this technique demonstrates that it could be used for a computer-aided mass screening of retinal diseases.

**Key Words—** Medical image processing, retinal images, hemorrhages detection, local variation operator, histogram-based thresholding.

## الخلاصة

تحليل صورة شبكية العين يستخدم بشكل واسع لكشف وتقييم مقدار اعتلال شبكية العين السكري. أن أولى علامات اعتلال الشبكية هي الجروح الداكنة اللون والمتمثلة بالنزف الدموي. هذا البحث يستعرض طريقة جديدة لكشف وتقييم مقدار النزف في الشبكية. الطريقة المقترحة لكشف مواقع الجروح تستند الى الدمج بين نتيجتي الفرز التقريبي والدقيق لمرشحات الجروح. عمليات الفرز التقريبي تعتمد على كشف حدود الجروح باستخدام خاصية تمايز حدودها مقارنة مع الاشكال الغامقة الاخرى. أما الفرز الدقيق للجروح فيستند الى استخدام المخطط البياني لعتبات المواقع المرشحة والتي تمتلك خصائص الجروح. تم توجيه وتدريب الطريقة المقترحة ومن ثم فحصها وتقييمها باستخدام بيانات من ١٥٣ صورة شبكية مجهزة مع نتائج تشخيص لطبيب مختص وان مقياسي الاداء (الحساسية ومقدار التنبؤ) هما ٩٠,٧% و ٨٥,١% على التوالي. بموجب الاداء المتميز للطريقة المقترحة، فأنها يمكن ان تستخدم على نطاق واسع لفحص وتقييم مرضى اعتلال الشبكية السكري.

**الكلمات المفتاحية:** معالجة الصور الطبية، صور شبكية العين، كشف نزف الشبكية، محدد المتغيرات المحلية، المخطط البياني لعتبات كشف الاشياء.

## 1. Introduction

Diabetic retinopathy (DR) is the main reason of vision loss in the world. Early defects of DR are harm to retinal vasculature leading to bloody lesions in the retina. This can result in several eye diseases namely, microaneurysms, hemorrhages (HEs), cotton wool spots and hard exudates. HEs are red lesions, which are the result of blood leakage and are signs of pathological retinas and the most widespread bloody lesions at early stages of DR. Weakening of retinal capillary wall and then the formation of HEs is caused by long standing of DR. Retinal vasculature disorder in majority of the patients with diabetes mellitus can be regarded as DR. Early screening of diabetic patients for the detection and quantification of DR can lessen the risk of vision loss in patients by around 50% [Kavitha and Duraiswamy, 2011].

The resemblance between features of the different lesions with the main structures of the retina, i.e. the blood vessels, the optic disc and the fovea can significantly affect the

efficiency of clinician's work to distinguish lesions from the retinal structures. Also the overlap between faint HEs and the retinal background as well as the low contrast between them make it difficult to discriminate these HEs from the background. Manual detection and grading, which are based on the experience of the clinician, are implemented in time-consuming and they may be susceptible to observer error.Thus, computer-aided DR detection and quantification from the retinal fundus photographs could facilitate more accurate and fast diagnosis and hence more effective treatment of DR.

The main aim of this work is to develop a computer-aided method as a part of medical screening scheme for detection and quantification of HEs. Color retinal images are widely used for the purpose of detection and quantification of different types of retinal lesions. Figure 1(a) illustrates normal retinal image with the main structures, while Figure 1(b) shows typical abnormal retinal image labeled with the main structures and two feature types of retinal diseases.

## 2. Related Works

Several techniques for detection of HEs have been proposed. Notable amongst these are those who utilized background estimation method to detect HEs [Zhang *et al.*, 2011]. In this method the area of interest, namely HEs and blood vessels, which should be clearly contrasted against the background, was determined. A classification of non-HEs caused by vasculature, was achieved by applying non-vessel inhibition operator to extract vasculature features. Then a multi-thresholds scheme is applied to help separate connective elongated vessels from scattered residual edge. Estimation of the background is obtained using a combination of Mahalanobis distance and a threshold technique to separate HEs and blood vessels from the background. Another automated method for the detection and quantification of DR was proposed using techniques of image analysis [Neera and Chandra, 2010]. This method has presented three techniques to detect three lesion types, namely HEs, microaneurysms, and hard exudates and assessed their severity based on their sizes and locations.

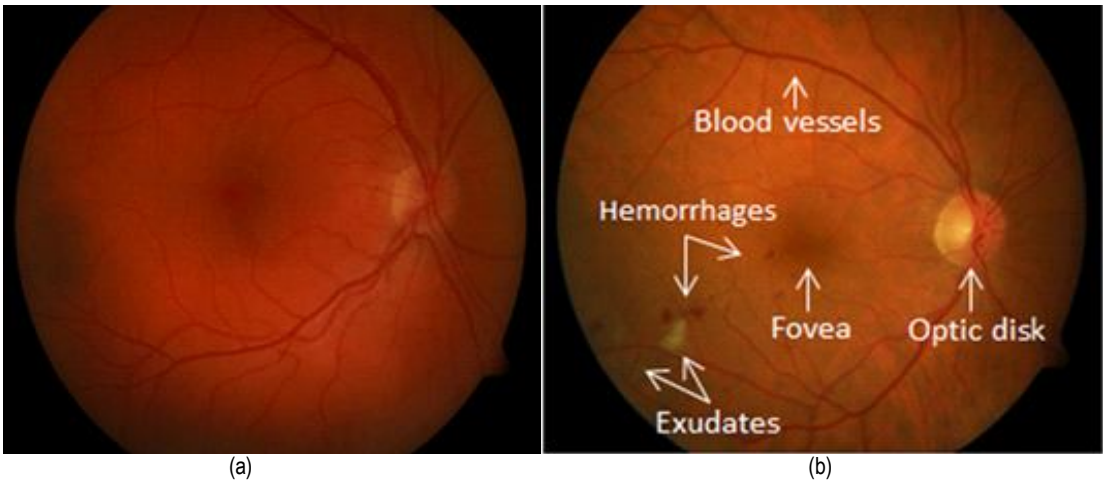


Fig. 1. (a) Normal retinal image. (b) Abnormal retinal image labeled with the main structures and two feature types of retinal diseases.

A new method for HEs detection was proposed, using splat feature classification [Tang *et al.*, 2011]. In this method the retinal image is segmented into many splats with same color. The procedure is based on assumption that the different splat pixels those have same structure have similar color. Each splat can be detected as a distinct feature, e.g. HEs. The classification process is based on training a classifier to recognize the splats with blood vessels and then to be used for extracting blood vessels, leaving real HEs candidates. Another method based on inverse segmentation to discriminate normal objects from abnormal objects was proposed [Köse *et al.*, 2011]. This method made use of the fact that the texture of normal objects does not vary as much as those of the abnormal objects. Then dark areas are left as real lesions (HEs) after using the intensity values whose intensity is lower than the background intensity value.

A method based on partitioning of color retinal images into non-overlapping segments covering the entire image has been presented [Tang *et al.*, 2013]. In this method, each segment has pixels of similar color and spatial location. To describe the segment characteristics relative to its locations, a set of features is determined for each segment, using responses from a variety of filter bank, interactions with neighboring segments, shape and texture information. An automated computer aided method for detection of HEs using fundus images was proposed [Bharali *et. al.* 2015]. In this work, blood vessels are detected and then eliminated followed by detection of HEs candidates. The method is applied on a variety of image databases and showed an overall accuracy of 97.3% and specificity of 98.9%.

## 3. Methodology

First of all, all images are resized to one of common standard sizes, i.e. the size of 640×480 pixels, thus, the algorithm can be applicable with all image resolutions. In the green component image, visual contrast of retinal structures and different lesion types are mostly better than the that in the other color retinal components [Walter *et al.*, 2002]. Hence, in this work, the green component of the color image has been used to extract HEs by three steps: Image enhancement using three operations, namely, shade correction, filtering, and contrast enhancement (Section 3.1), preliminary HEs segmentation by calculating local variations of all image regions (Section 3.2), and refining results of preliminary step using histogram-based thresholding (Section 3.3).

### 3.1. Image Enhancement

Retinal images mostly suffer from non-uniform illumination and sometimes from low visual contrast, as in most of the camera-acquired images. Therefore, operations of image enhancement aim to prepare the image with better qualities using shade correction, filtering, and contrast enhancement. Non-uniform illumination could be corrected using mathematical morphology techniques. A morphological top hat with structuring element of disk shape was found effective for shade correction. The morphological top hat acts to produce smooth estimation to the background of the green channel component. It is based on morphological opening and closing with suitable size of structuring element to avoid completely fitting to the small candidate objects. Then the approximated background $M(I)$ is subtracted from the raw green component image ($I$) to produce a new image $(I')$ with reasonable uniform background. This operation can be formulated as follows:

$$I' = I - M(I) \quad (1)$$

To get rid of unexpected dark regions at the boundaries and near the fovea, alternating sequential opening and closing were used to calculate the approximation of the background as follows:

$$M(I) = \beta^{ns}\{\lambda^{ns}[\beta^{1s}(\lambda^{1s}(I))]\} \quad (2)$$

where $\beta$ refers to opening operator, $\lambda$ refers to closing operator, $s$ refers to structuring element and $n$ refers to the number of alternative repetition, $s$ is used as a disk structuring element with radius of 7 pixels and $n$=10 . Success rate of the shade correction operation depends dramatically on the image non-uniformity grade and on the suitability selection to the size and shape of structuring element.

Due to non-uniform illumination conditions of the imaging system, ambiguity may be introduced to the image with a form of imprecise values and then low visual contrast. Consequently, An existing fuzzy enhancement algorithm, called "minimum of fuzziness algorithm" was applied to enhance the contrast of image features, and this algorithm is described in a previous work [Jaafar *et al.*, 2011]. The selection of this algorithm is based on that it is simple to implement and is not expensive computationally. For its clarity and immediate relevance, some aspects are summarized below. The gray-levels of the green channel component after the shade correction $(I'_{mn})$ are fuzzified by the membership function as in the following equation:

$$F(I'_{mn}) = \mu_{mn} = [1+(I_{max} - I'_{mn})/D] - E \quad (3)$$

where the parameters $E$ and $D$ denote the exponential and denominational fuzzifiers respectively, suitable value of $D$ is determined based on the transition point of the membership, where value of $E$ is commonly taken up to 2. To modify the membership values, the intensification operator $N_1$ is applied on the membership function and successive application of the nonlinear transformation $(N_j)$ is used to enhance the membership function as follows:

$$N_j(\mu_{mn}) = N_1[N_{j-1}(\mu'_{mn})] \quad j = 1,2,3,\cdots \quad (4)$$

where $j$ represents the number of iterations to allow the user getting appropriate level of enhancement.

A new gray level can now be generated from the modified membership values using inverse membership function as in the following expression:

$$I''_{mn} = I_{max} - D[(\mu'_{mn})^{-0.5} - 1] \quad (5)$$

Where $I''_{mn}$ represents the gray levels of the enhanced image. Figures 2(a) and 2(b) show a color retinal image and its green component image. Figures 2(c) and 2(d) show the shade corrected image and contrast enhanced image respectively.

### 3.2. Preliminary HEs Segmentation

Most retinal images contain dark and bright regions with similar features of dark and bright lesions. However, most of these areas have no distinct borders, while real dark lesions like HEs have distinct and clear edges but in different grades depending on the severity grade of DR. This feature could be utilized to extract HEs using computation of local variation of each pixel and then obtaining the standard deviation image. The standard deviation image represents main characterization of closely distributed clusters of HEs. As some contrasted blood vessels have similar features of HEs, they should be

eliminated before using the local variation operator. A closing operator was then applied on the enhanced image $(I'')$ using structuring element $(se)$ of 8 pixels radius. Resulting image could be symbolled by $I_1''$ as follows.

$$I_1'' = C^{se}(I'') \quad (6)$$

where $C$ refers to the closing operator. Calculation of local variation could be represented by the following equation, and the resulted image is symbol by $I_2''$:

$$I_2'' = \frac{1}{N-1} \sum_{h \in w(y)} (I_1''(h) - \sigma(y))^2 \quad (7)$$

where $y$ refers to a set of pixels in a sub-window $w(y)$, $N$ is the number of pixels in $w(y)$, $\sigma(y)$ denotes the mean value of $I_2''(h)$ and $h \in w(y)$. Selection of window size is based on required balance between performance measures, namely sensitivity and predictive values. Experimental tests have showed that the window size of 9 × 9 pixels is suitable for competitive performance. Automatic Otsu's thresholding was then applied to the standard deviation image to eliminate objects of low local variation [Otsu, 1979].

To classify extracted candidates into artifacts (non-HEs) and real HEs, prior knowledge about HEs features, namely minor and major axis lengths, solidity and area were used to discriminate real coarse candidates. Values of features and limits in their relationship were used to help discriminating and removing non-HEs easily. Examples of these characteristics are narrow and long areas related to the residual vasculature. To make sure that most of real HEs pixels are available within extracted candidate regions a dilation process was applied to the resulted image, and the suitable structuring element is disk-shaped of 5 pixels radius. Then a clear border process was implemented to the resulting image to eliminate retinal structures whose level are lower than those of surrounding pixel level and connected with the image border.

**3.3. Refining of Segmented HEs**

Global thresholding is very suitable method for fast and easy image segmentation. If input image is of poor quality or non-uniform illumination, global thresholding may result in low segmentation accuracy. Hence adaptive local thresholding is suitable alternative to achieve segmentation results with better segmentation accuracy. Due to re-computing operations to each local region, the main disadvantage of adaptive thresholding is the slow running speed. Adaptive thresholding has been implemented on the basis of applying local thresholding followed by global thresholding. The local thresholding was implemented using the technique of image splitting into homogenous sub-images and the sub-image number depends on uniformity of the original image. In the global thresholding, histogram-based thresholding was used with each homogenous sub-image to extract desired candidates.

The refining stage includes two processes: First, image is partitioned into number of sub-images using a technique of pure-splitting. In the second process, a histogram-based thresholding is used to segment desired candidates in each resulting sub-image. The optimal number of image partitions is not fixed and dependent on uniformity of original image. Procedures of pure splitting method is based on considering the whole image as initial segmented image. The whole image is partitioned into quarters followed by testing homogeneity of each part if any of the quarters is not homogeneous, it is again partitioned into quarters and so on until achieving homogeneity for all sub-images.

The procedures of pure splitting method, proposed by Lee [Lee, 1986], was followed in this work, but in different approach for testing homogeneity of resulting sub-images.

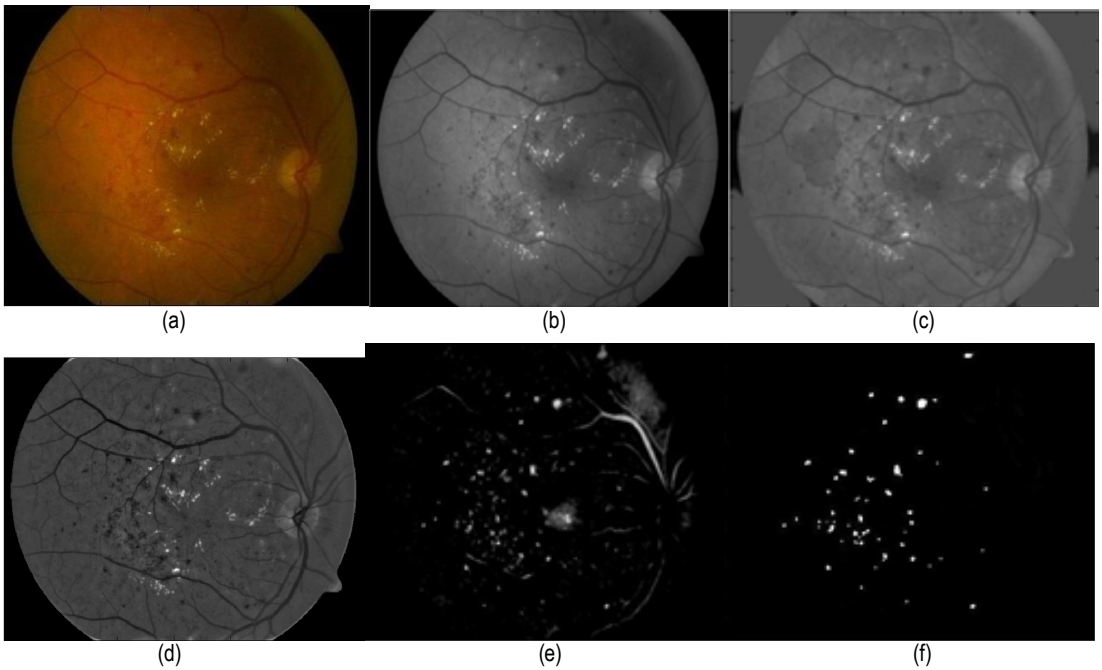


Fig. 2. Example on the methodology steps. (a) Original image. (b) Green component image. (c) Image after shade correction. (d) Image after contrast enhancement. (e) Preliminary segmentation of HEs. (f) Result of the final HEs segmentation (Refining step).

The work principle of the proposed pure splitting method is based on successively partitioning each segment into two equal sub-segments, if it is not homogeneous enough. The main reason of partitioning the image into two sub-images, instead of quarters, is to dispose of merging step that is needed in the four quarters approach. In addition, the other advantage of partitioning into two parts is that the total number of resulting sub-images may be in some cases smaller than that in the quarters approach and as a result it will be implemented with lower computational complexity.

In the pure splitting, a statistical hypothesis test was applied in homogeneity test for each sub-image based on parameters which are extracted from image features. Image features are used to create parameters to be then used as constraints in the statistical hypothesis test. Suitable image for creating features and then constraints is the green component image after eliminating the vasculature, optic disk and suppressing the black background around the retina.

To achieve fine HEs, histogram-based thresholding was applied to the locations of homogeneous sub-images, which are obtained in the pure splitting step. Let a segment of the preliminary segmented image is defined as a subset of $I_a''$ with respect to uniform lighting criterion. Hence applying automatic thresholding ($T$) on the image considering variable threshold $(\varepsilon)$ where $\varepsilon$ value relies on individuality of each sub-image. Resulting image can be represented by $I_a''$ as follows:

$$I_a'' = \sum_{i \in k} T_{\varepsilon i}\{(I_a'')_i\} \qquad (8)$$

where $k$ represents the number of homogeneous sub-images.

## 4. Results and Performance Evaluation

The proposed method has been trained and tested using normal and abnormal retinal images from a variety of publically available databases. In addition, a lot of experiments have been implemented to validate the proposed method using a set of retinal images with their clinician's annotated images. A set of 153 retinal images from a different sources was used in this work and as below:

• A set of 89 retinal images with size of 1500×1152 pixels was supplied by the DIARETDB1 database with their clinician hand-labeled images. This set was used to train and test the HEs results in pixel-based [Kauppi *et al.*, 2007], where 47 images of this set includes HEs, while the other 42 images are normal or contain other lesion type.

• A set of 30 retinal images with size of 640×480 pixels from the Messidor database with their hand-labelled images was used to validate the proposed method [Walter, 2002].

• A set of 34 normal images from the Drive database with size of 565×584 pixels was used to measure the proposed method success rate in discriminating normal images from other abnormal images [Staal *et al*., 2004].

Clinician's annotated data was used to assess the proposed method quantitatively by comparing their results in both levels, i.e. pixel calculation and image classification. Assessing the method performance requires calculation of four types of pixels. These are; true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). These pixels are calculated for each binary image after the detection process and then quantitatively compared with the binary annotated images to measure the performance measurements, namely sensitivity, specificity, accuracy and predictive value.

In the validation processes a set of 77 images with their clinician's annotated images from both DIARETDB1 and Messidor databases was used in pixel-based calculation. The proposed method achieved 90.7%, 97.9%, 98.5% and 85.1% of sensitivity; specificity; accuracy; and predictive value respectively. A set of 76 normal retinal images from the Drive and DIARETDB1 databases was used to assess the proposed method in terms of normal and abnormal classification and achieved a success rate of 97%. To evaluate the proposed method performance with respect to different related woks, a set of pathological 47 retinal images (contain HEs) from DIARETDB1 database was used to compare between measurements of the proposed method and previous related works in pixel level. Table 1 presents the measurements of the proposed method and some robust related works. From a comparison between these measurements, there appears superior predictive value of the proposed method, which represents the most meaningful measure. It also shows a competitive sensitivity compared with those in the related works.

Table 1. Comparison between measurements of the proposed method and some related works in pixel-based.

| Reference | Sensitivity.% | Specificity.% | Accuracy % | Predictive value% |
|---|---|---|---|---|
| Zhang *et al*. 2011 | 88.2 | 97.4 | 98.7 | 83.2 |
| Kose *et al*. 2012 | 90.3 | 96.8 | 97.1 | 81.7 |
| Bharali *et. al.* 2015 | --- | 98.9 | 97.3 | --- |
| Proposed method | 90.7 | 97.9 | 98.5 | 85.1 |

To demonstrate the significance of the refining step in the detection of HEs, a comparison between the preliminary segmentation result (shown in Fig. 2(e)) and the final detection of HEs (shown in Fig. 2(f)) was implemented quantitatively. The

quantitative comparison demonstrates that the refining segmentation step has had a noticeable importance in removing artifacts from the final segmented image. ROC for of the proposed algorithm is shown in Figure 3, and illustrates a compromise between the desired pixels (TP) and undesired pixels (FP) by changing the parameters of threshold value and parameters from the image characteristics in homogeneity test of sub-images.

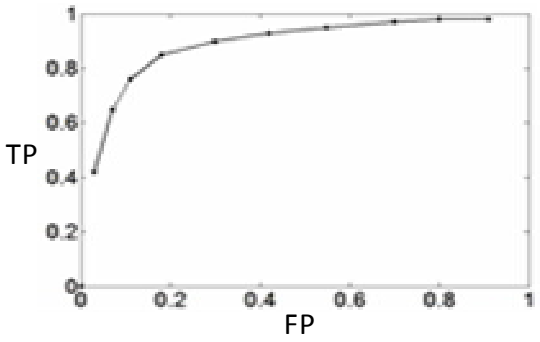


Fig. 3 ROC of the performance for different parameters.

## 5. Conclusions

The proposed method is adapted to detect hemorrhages. using sets of images from different databases and a variety of image qualities so that it could be applicable with different range of image sizes and qualities. It is designed with taking most image features and information into account, thus making the classification of real hemorrhages easier and faster. In comparison with distinctive related works, the proposed method shows an improvement in the sensitivity and predictive value, while specificity and accuracy are reasonable compared with the those of the distinctive methods.

The performance results of this work demonstrated that the technique of image partitioning along with the histogram-based thresholding is very efficient approach to detect hemorrhages with superior performance. Robustness of this work comes from using optimal computed parameters which are extracted from image information. A limitation of the proposed method is its limited ability to get rid and remove all spurious objects those have resemblance features to real hemorrhages.

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## References

Bharali, P., Medhi, J. P., and Nirmala, S. R. ,2015, Detection of hemorrhages in diabetic retinopathy analysis using color fundus images. IEEE 2nd International Conference on Recent Trends in Information Systems (ReTIS), p.p 237-242.

Jaafar H. F., Nandi A. K., and Al-Nuaimy W.,2011, Decision support system for the detection and grading of hard exudates from color fundus photographs," J Biomed Opt, vol. 16, 116001, p.p 1-10.

Kauppi T., Kalesnykiene V., Kamarainen J. K., Lensu L., Sorri I., Raninen A., Voutilainen R., Uusitalo H., Kalviai-nen H. and Pietila J. ,2007, DIARETDB1 diabetic retinopathy database and evaluation protocol, Technical report, Faculty of Medicine, University of Kuopio, Finland.

Kavitha S., and K. Duraiswamy K. ,2011, Automatic Detection of Hard and Soft Exudates in Fundus Images Using Color Histogram Thresholding. European Journal of Scientific Research,Vol.48 No.3, p.p 493-504.

Köse C., Şevik U., Ikibaş C., Erdöl H. ,2012, Simple methods for segmentation and measurement of diabetic retinopathy lesions in retinal fundus images, Computer Methods Programs Biomed., vol. 107(2), p.p 274-293, DOI: 10. 1016/j. cmpb. 2011. 06.007.

Lee C. H. ,1986,Recursive region splitting at hierarchical scope views, Vision Graphics Image Process., vol. 33, p.p 237-256.

Neera S., and Chandra R. ,2010, Automated early detection of diabetic retinopathy using image analysis techniques, International Journal of Computer Applications (0975 – 8887), Vol. (8), No. (2), DOI: 10.5120/1186-1648.

Neimeijer M., Ginneken B.V., Staal J., Suttorp-Schulton M.S. and Abramoff M.D. ,2005, Atomatic detection of red lesions in digital color fundus photograph, IEEE Transaction on Medical Imaging, 24(5), p.p 584-592.

Otsu N. ,1979, A Threshold Selection Method From Gray-Levels Histograms, IEEE Trans. Systems, Man, and Cybernetics, vol. 9(1), p.p 62-66.

Staal J., Abramoff M. D., Niemeijer M., Viergever M. A., and van Ginneken B., 2004,Ridge based vessels segmentation in color images of the retina, IEEE Transaction on Medical imaging, vol. 23, p.p 501-509.

Tang L., Niemeijer M., Abràmoff M.D. ,2011, Splat feature classification: Detection of the presence of large retinal hemorrhages, in: 8th IEEE Int. Symp. Biomed. Imaging: From Nano to Macro, p.p 681-684, DOI: 10.1109/ISBI.2011.5872498.

Tang L., Niemeijer M., Abràmoff M.D. ,2013, Splat Feature Classification with Application to Retinal Hemorrhage Detection in Fundus Images, IEEE Transactions on Medical Imaging, Vol. (32), No. (2), p.p 364 – 375, DOI: 10. 1109/ TMI. 2012. 2227119.

Walter T., Klein J. C., and Massin P. ,2002, A Contribution of image processing to the diagnosis of diabetic retinopathy detection of exudates in color fundus images of the human retina, IEEE Trans. Med. Imaging, 21, p.p 1236-43.

Zhang D., Li X., Shang X., Yi Y., and Wang Y.,2011, Robust hemorrhage detection in diabetic retinopathy image, 1st ACPR2011, p.p 209-213, DOI: 10. 1109/ ACPR. 2011. 6166529.