Automatic Abnormal Structures Localization From Diabetic Retinopathy Images Using Differences In Intensity Values

Raad Alwan

Abstract: Diabetic patients require annual screening to prevent the infectious of Diabetic Retinopathy (DR) which cause blindness in the working ages. The dramatic dissemination of this disease all over the world turns the process of diagnosing and monitoring DR lesions to be time and effort consuming and the need to design an automatic system that has the ability to localize DR lesions and specify their type is indispensable. This paper presents a new technique that automatically localize all three DR lesions, exudates, hemorrhage and cotton wool by emphasizing the differences in intensity values of these lesions. Removing the optic disk is a preprocessing step to remove the effect of its intensity value on other structures; followed by highlighting each lesion type through consequent steps; and ending with localizing the lesions distinguishably. After intensive testing through five different datasets with more than 1500 images, the proposed technique achieved 98.99, 99.3, and 89.44 for accuracy, sensitivity, and specificity, respectively, which makes it to be competitive among several proposals.

Index terms: Diabetic Retinopathy, fundus image, intensity value, exudate, hemorrhage, cotton wool.

1. INTRODUCTION

Diabetes is a chronic disease that affect different organs and change the patient's life. One of the most important effect of this disease is the damage that is caused to the retina which results in blindness to patients at working age in developing countries, a case called Diabetic Retinopathy (DR) [1, 2]. Since this disease is asymptomatic during its first stages, the only way to detect DR is the regular annual screening for the retina (fundus image (FI)) to discover whether any kind of lesions are produced where the number, type, and location of these lesions determine the level of DR. Micro aneurysms appeared in the early stages when blood vessels fail in nourishing the retina because of their blockage which appear as small red dots in FI. In later stages, the need of generating new vessels appeared so the body produce them but with thin fragile walls that exposed to blood leakage producing hemorrhage which can cause severe vision lose or even complete blindness. These type of lesions are appeared as red circles in FI. Exudates, which appear as white lesions in FI, are lipid cells leak from the new produced vessels. They can be either hard yellowish lesions with clear boundary or soft with no regular shape or clear boundary (Cotton wool spots) [3]. **Error! Reference source not found.** exemplified a fundus image with all types of DR lesions beside normal anatomical structures as optic disc (OD), fovea, and optic nerve.

- *Raad Alwan is currently an assistant Prof. in the department of Computer Science, Faculty of Information Technology-Philadelphia University, Jordan, 19392. E-mail: ralwan@philadelphia.edu.jo.*

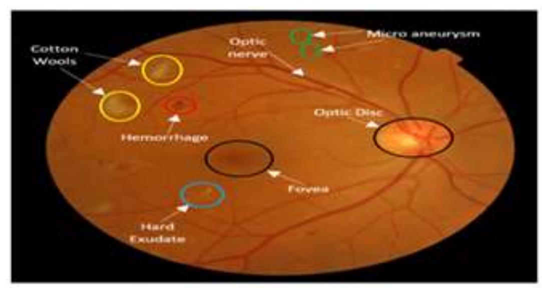

Figure 1: A fundus image illustrating all types of diabetic retinopathy lesions.

Because of the increasing number of diabetics and the decreasing number of ophthalmologists [4], the process of screening diabetic patients regularly adds more effort and it considered to be time consuming. For this reason several automatic DR detectors were proposed through the past decade.

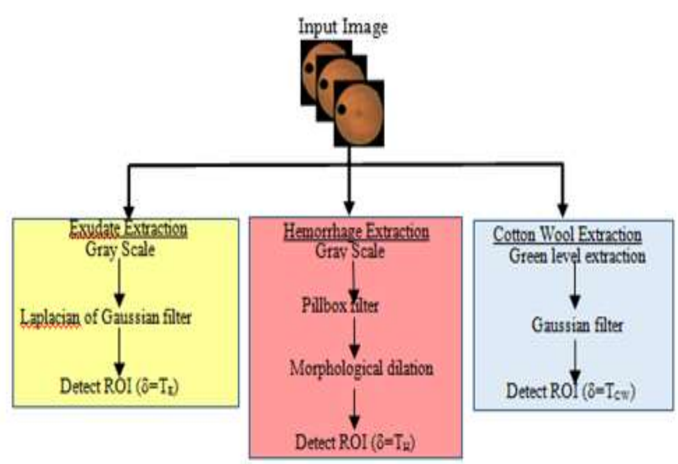

Figure 2: Block diagram of the proposed lesion detection system.

In the early years, Sinthanayothin C. et al. proposed a new technique that depends on removing the basic structures of the FI such as optic disk, fovea, and optic nerve in order to focus on extracting other lesions using different color bands [5]. Based on morphological features and gray color contrast, Thomas Walter et al. proposed their work in 2012 and achieved better sensitivity in locating exudates [6]. In 2003, Usher D. et al. used Neural network to classify different types of lesions after preprocessing steps [7]. Depending on Bayesian classification technique, Harihar N. proposed their work in 2006 to classify the abnormal structures to either exudates or micro aneurysms [2]. Some of the fundus images are not clear and have no noticeable contrast. To deal with this kind of images, Sopharak A. et al proposed their work to locate exudates based on morphological properties and using low computer specifications to be used in poor areas in developing countries with lack of experts in the field [8]. Echo State Neural Network was used in [9] to distinguish between normal and pathological lesions after preprocessing the image followed by contextual clustering process to segment some regions of interest. On their work, Usman A. and his colleagues proposed to select the candidate regions based on filter banks after preprocessing the image and removing normal structures. Later these candidates were examined according to some features such as area and statistics to choose the required lesions [10]. Although some proposals worked on low quality images, in their work, Imani et al. proposed a technique that extract RD lesions from only good quality images [11]. After preprocessing these images, morphological features applied to distinguish between all the regions of interest. In 2016, several proposals were published. As examples, [12] used intensity transformation and multi-level histogram analysis to extract red and white lesions respectively, and [13] used conventional neural network to achieve the same goal. In the later year, [14] segmented the required lesions using mathematical morphologies, and [15] graded the level of DR using multi-scale line. This paper proposes a new technique to localize all the three types of DR lesions based on the intensity value of each type. Since OD usually is the brightest region in the fundus images, the proposed technique first remove this structure using fast and accurate algorithm. After passing through subsequent steps, each type of DR lesions can be highlighted and localized.

2. METHODOLOGY

The process of extracting all different kinds of pathologies from an FI cannot follow the same localization/segmentation algorithm due to the differences in their statistical and morphological features [11]. The design of the proposed system passes through subsequent stages, starting from preprocessing FI followed by the steps leading to localize exudates, hemorrhages, and cotton wool spots. These steps are detailed in the following sections and **Error! Reference source not found.** illustrates these stages.

A. Preprocessing stage

The main aim of this stage is to remove the OD in order to focus on the pathological lesions, since OD usually has the brightest color in the fundus images and removing it reduce the distraction from other lesions. To achieve this goal, the algorithm proposed in [16] is used and it is chosen for several reasons. Firstly this algorithm is the fastest among several proposed algorithms; secondly, it achieved high ratio of sensitivity, specificity and accuracy; and thirdly, the algorithm was tested on more than 1500 fundus images taken from different data sources using different cameras with different fields of view. **Error! Reference source not found.** illustrates the stages of locating and extracting OD. The last stage is to change the located OD into background to ignore it throughout the forthcoming stages since it is not one of the regions of interest (ROI).

B. Extracting Exudates Stage

Hard exudates appear in the early stages of DR as yellow blots in FI (**Error! Reference source not found.** (a)). To extract these pathologies, gray scale is applies on the input image using Eq. (1) and Eq. (2) which summing its weighted color components (**Error! Reference source not found.** (b)). Applying Laplacian of Gaussian filter (LoG) is the second step which is chosen since it is used to find areas with rapid changes, a feature of hard exudates with regular shape and clear boundaries. LoG is a derivative filter, illustrated in Eq. (3), and applied using ($\sigma = 0.3$) to the gray scale image with intensity $I(x, y)$ and the result of this step is in **Error! Reference source not found.** (c).
Determining the ROI is done base on converting the image to black/white using Eq. (4) using a threshold value (T_E). [17]The result of this step alongside with the final result are in **Error! Reference source not found.** (d) and (e) respectively.

$$I_{Gray} = 0.2989 * I_R + 0.5870 * I_G + 0.114 * I_B \quad (1)$$

$$I(x, y, I_{Gray}) = I(x, y, I_R, I_G, I_B) \quad (2)$$

$$LoG(x, y) = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3)$$

$$g(x, y) = \begin{cases} 1 & LoG(x, y) \le T_E \\ 0 & LoG(x, y) > T_E \end{cases} \quad (4)$$

C. Extracting Hemorrhage Stage

Since they are blood leakage from the capillaries, hemorrhages appear in FI as red dots and blots with almost circular shape. After applying the gray scale convertor in Eq. (1, 2), pillbox filter is applies using Eq. (5) and R=15. This type of filters finds the circular averaging within the square matrix of side=2*R+1. Applying circular dilation as in Eq. (6), where ($\oplus$) the circular dilation (c) with radius=10. **Error! Reference source not found.** illustrates the steps of extracting hemorrhages.

$$P(I) = \begin{cases} 1 & k < R \\ 0 & K \ge R \\ {}^{1}\!/_{2} - \frac{I-R}{{}^{1}\!/_{2}} & otherwise \end{cases} \quad (5)$$

$$f2(x, y) = f1(x, y) \oplus c \quad (6)$$

D. Extracting Cotton Wools Stage

This type of pathologies are appeared as white blots, a case which make them much clearer on green level and applying Gaussian filter, illustrated in Eq. (7). Extracting ROI in this step is based on Eq. (4) except of that the using threshold is (T_{CW}). **Error! Reference source not found.** shows the steps of extracting cotton wools from a fundus image.

$$G(x, y) = \frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (7)$$

3. Results and comparisons

A. datasets

The proposed approach are tested using five different datasets, with total number of image= 1535, in order to evaluate it in terms of different factors. **Error! Reference source not found.** lists the used datasets alongside with their properties.

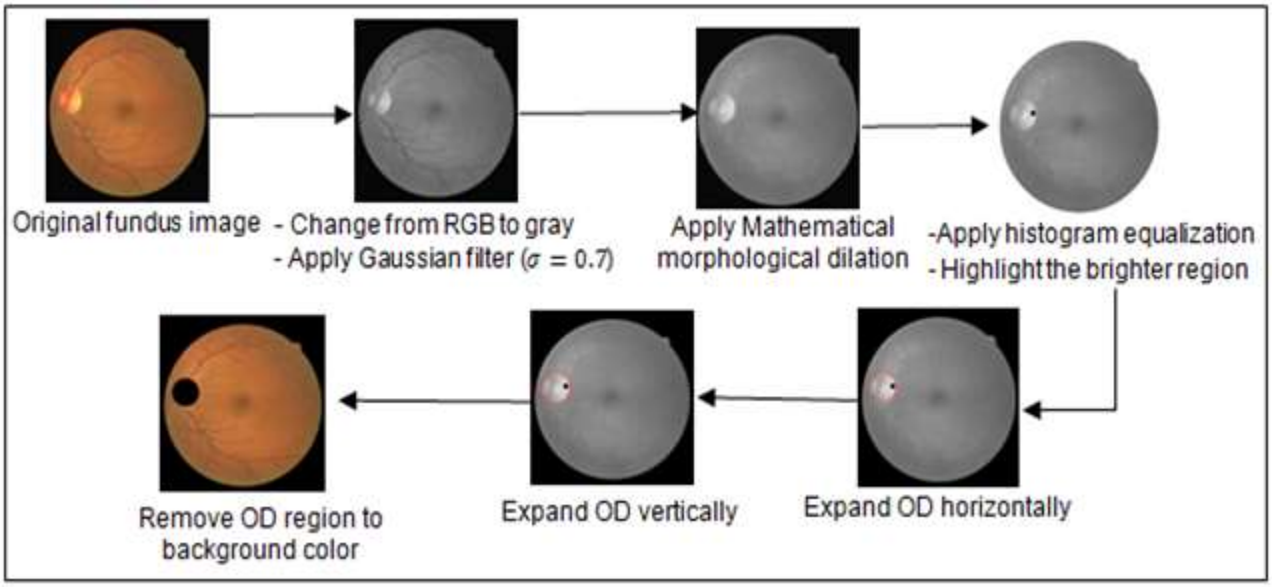

Figure 3: steps of the preprocessing stage to remove OD.

Table 1: Databases used in evaluating the proposed technique and their properties.

Data sets / Properties	MESSIDOR [18]	DRIVE [19]	STARE [20]	DIARETDB0 [21]	DIARETDB1 [22]
# Normal images	547	33	31	20	5
# Pathological images	653	7	50	110	84
# Total images	1200	40	81	130	89
Resolution	1440X960	565X584	605X700	1500 × 1152	1500 × 1152
Field Of View	45°	45°	35°	50°	50°

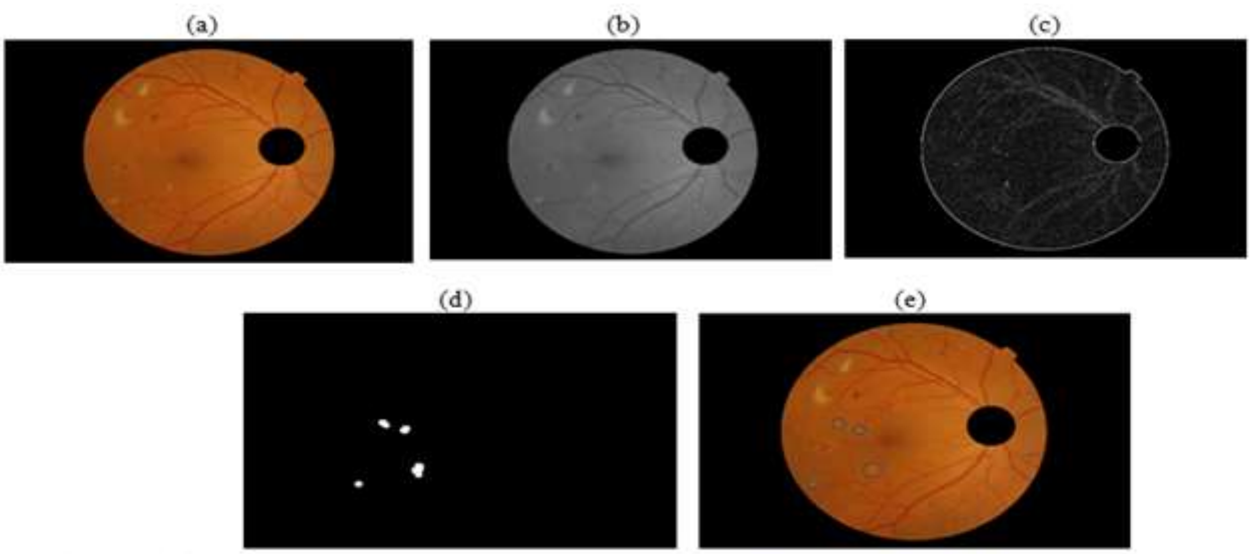

Figure 4: The steps of extracting hard exudates from a fundus image. (a): original image, (b) gray scale, (c) applying LoG filter , (d) find ROIs, and (e) final results.

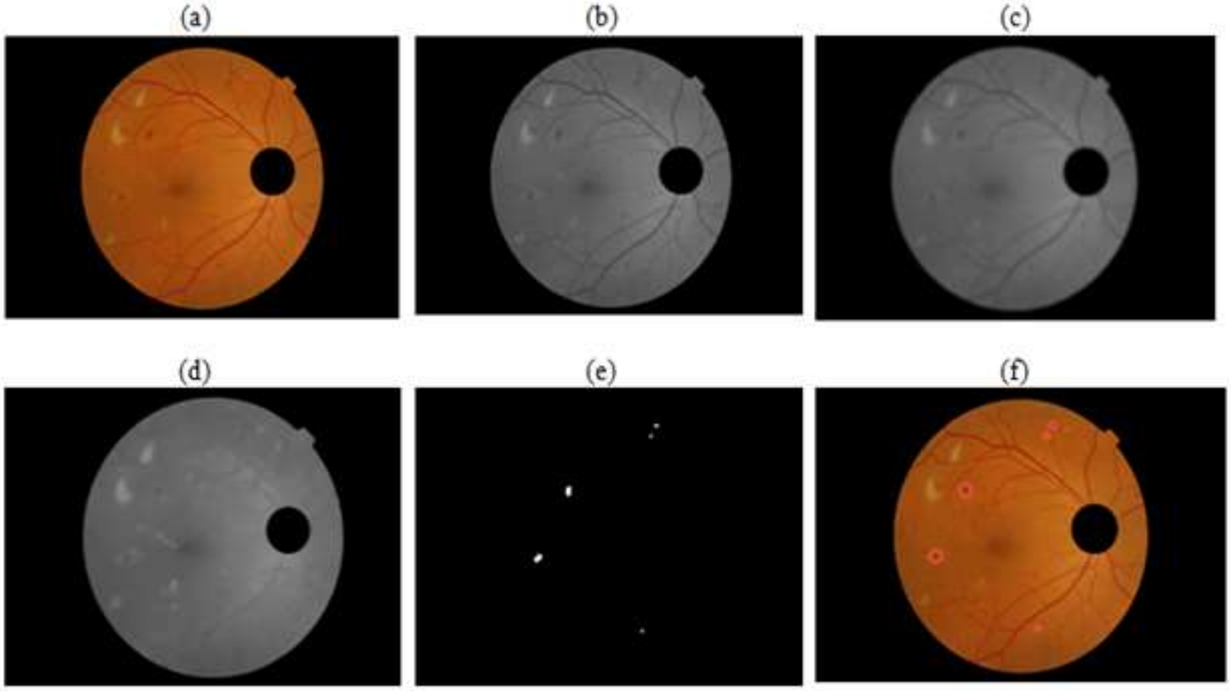

Figure 5: The steps of extracting hemorrhage from a fundus image. (a): original image, (b) gray scale, (c) applying pillbox filter, (d) applying morphological dilation, (e) find ROIs, and (f) final results.

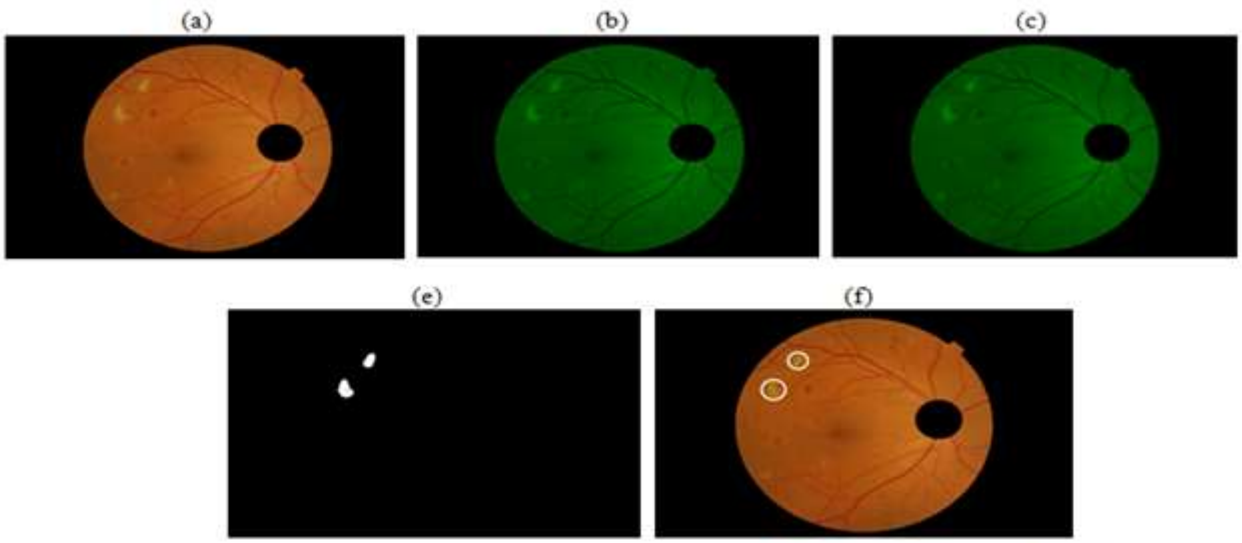

Figure 6: The steps of extracting cotton wools from a fundus image. (a): original image, (b) green level, (c) applying Gaussian filter , (d) find ROIs, and (e) final results.

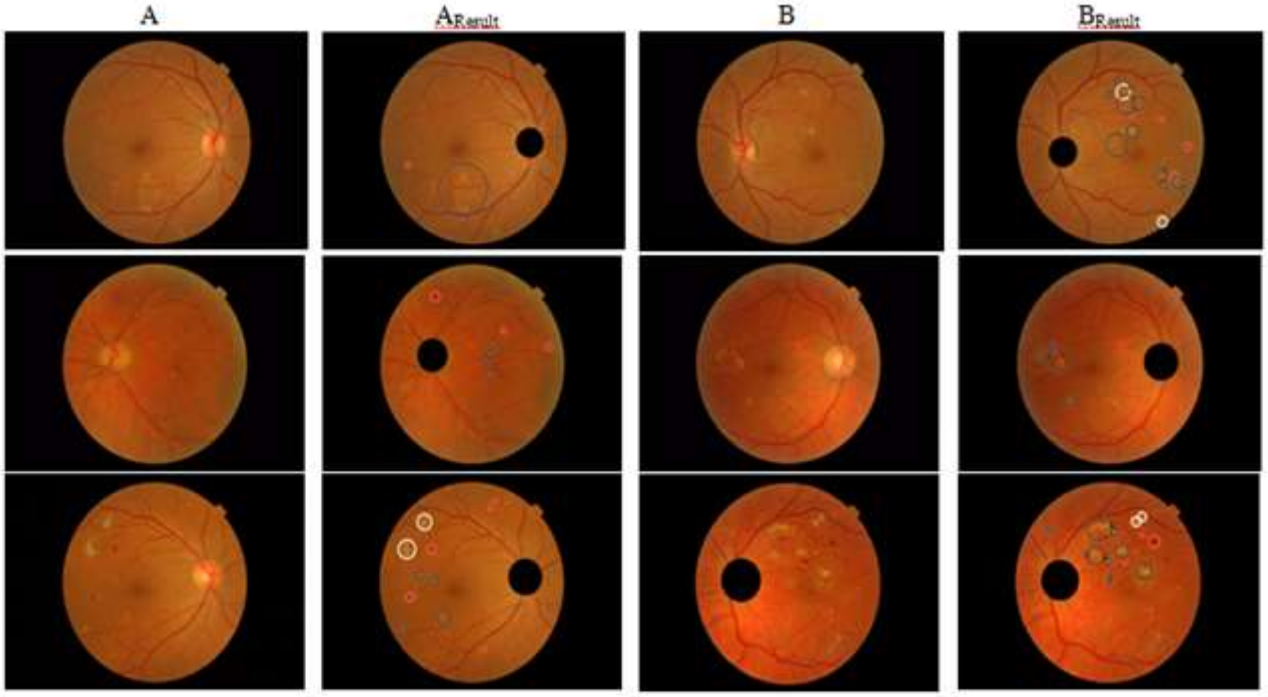

Figure 7: Sample results of applying the proposed system on fundus images taken from MESSIDOR dataset. Columns A and B are the original images, while columns A_{Result} and B_{Result} are the final outputs.

E. Results

This section presents the evaluation technique of the proposed system based on some factors. Accuracy is one of the most important factors to evaluate medical diagnosis system. This factor measures ratio of successfully localized lesions to the whole actual number of lesions, as seen in Eq. (8). Another important factors are sensitivity and specificity which measure the true positive rate and the true negative rate, as shown in Eq. (9, 10), respectively. **Error! Reference source not found.** contains selected pathological fundus images listed in columns (A) and (B). The results of applying the proposed technique are listed in columns (A_{Result}) and (B_{Result}) in which exudates, hemorrhage, and cotton wools are circled with black, red, and white respectively.

$$Acc(x) = \frac{x_{sucess}}{N} \quad (8)$$

$$sensitivity = \frac{TP}{TP+FN} \quad (9)$$

$$specificity = \frac{TN}{TN+FP} \quad (10)$$

F. Comparisons

As mentioned earlier, several techniques were proposed to detect and segment DR lesions for the purposes of diagnosing and monitoring the patients. **Error! Reference source not found.**lists some of the proposed technique alongside with the tested factors as mentioned in the literature. Our proposed technique is considered to be competitive compared it with other proposals in terms of sensitivity and specificity. Moreover, it has higher accuracy rate among several proposals and requires less time to be processed, the features that makes it compete with others.

Error! Reference source not found. lists the evaluation factors percent for the proposed algorithm. The average accuracy through all the used datasets is 98.99 which makes the proposed technique to be accurate and dependable. The least accuracy value was when dealing with STARE dataset images since their field of view is 35° which makes these images require different processing. The average sensitivity ratio, which equals to 95.3, turns the proposed technique to detect the actual DR lesions (high true positive) with low ratio of detecting non DR lesions as actual lesions. On the other hand, specificity ratio of 91.6 decreases the number of undetected DR lesion.

Table 2: The results of evaluation factors on the proposed technique

Dataset / factor	MESSIDOR	DRIVE	STARE	DIARETDB0	DIARETDB1
Accuracy%	99.7	99.3	97.9	98.8	99.2
Sensitivity%	97.4	96.8	91.3	95.8	95.3
Specificity%	94.2	89.8	88.4	92.7	93.0

4. CONCLUSIONS

This paper proposed a new technique to localize abnormal pathologies in Diabetic Retinopathy (DR) fundus images. DRis the main cause of blindness for diabetic patients without regular monitoring and eye screening because of the effect of these pathologies on the retina. Based on the fact that each type of abnormal structures appear in the fundus image in specific color intensity, shape, and size, the proposed technique highlight each of them after passing the image through several steps. After intensive testing through five datasets, the proposed technique achieved competitive results in term of accuracy, sensitivity and specificity ratios. Although the accuracy rate can be increased by using morphological features of each pathology such as area and location. It can be used effectively in deciding the level of DR depending on some statistical information that can be derived from the results of the proposed technique.

Table 3: comparing the proposed technique with other proposals.

Author	# tested images	Sensitivity	specificity
Sinthanayothin C. et al. [5]	30	83	94.2
Thomas Walter et al. [6]	15	92.8	-
Usher D. et al. [7]	1273	95.1	78.9
Narasimha H. et al. [2]	43	97	99.3
Sopharak A. et al. [8]	60	80	99.5
[9]	50	93.0	100
Usman A. et al. [10]	1410	97.83	98.36
Imani et al. [11]	1200	92.01%	95.45
Amin et al. [14]	1400	98.5	-
Proposed method	1535	99.3	89.44

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