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METHODOLOGY FOR IDENTIFICATION AND CLASSIFICATION OF MICROANEURYSM FROM RETINA IMAGE

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Abstract: Diabetes is spreading at a very fast rate these days hence a threat to many comorbid conditions occurring with diabetes is increased. One of the complications of diabetes includes a retinal disorder called Diabetic Retinopathy (DR). In DR, the increased blood sugar level damages the retinal blood vessels which result in permanent or partial blindness. Microaneurysms (MA) are smaller capillary swellings of the retina of a person suffering from Diabetic Retinopathy. These are the very first evidence of the presence of Diabetic Retinopathy. Thus accurate detection of these lesions will help in early detection of DR. The paper describes a simple automated approach for MA detection from fundus images. In total, a set of 46 images collected from a local eye hospital is used for training and testing of the algorithm. The algorithm is described in three processing steps. The first stage involves conditioning the input image into a suitable form for further process. Second stage extracts all possible components from the conditioned image which can be the possible candidate for MA. The third stage involves feature extraction and classification of true lesions from false candidates. Out of a set of 46 images, 31 images are used for training the classifier and 15 images are used for testing purpose. The algorithm achieved the sensitivity of 88.83%, specificity of 88.67%, and accuracy of 89.33%.

Keywords: Automated Approach; Microaneurysm; Naive Bayes Classifier; Diabetic Retinopathy.

1. INTRODUCTION

Diabetes has become a serious health issue that is affecting a mass population, especially in the middle-income countries. The world leaders are planning to focus on diabetes as one of the four prime concerned Noncommunicable Diseases (NCD). The excess sugar level in the blood of a diabetic patient severely affects his/her retinal blood vessels in the course of time. The intense damage to the retina can cause irreversible blindness to these patients. The medical term for this damage is called as Diabetic Retinopathy (DR).

Diabetic Retinopathy progression has two main stages: (1) Non-Proliferative Diabetic Retinopathy and (2) Proliferative Diabetic Retinopathy. First is the early stage in which blood vessels leak fluid or bleed distorting the vision. In second stage many abnormal vessels grow on the retinal surface causing scarring and cell loss.

We can prevent the irreversible visual impairment occurring due to DR by diagnosing the disease at early stages and proper medications. Early stages of the disease show very subtle symptoms and patients may not recognize them until vision distortion is started. Thus, regular consultations with expert ophthalmologists are necessary to avoid any threat to vision. But the number of diabetic patients requiring ophthalmologist's assistance is huge as compared to the number of ophthalmologists available. In order to reduce the workload of eye experts, automated systems should be introduced which can accurately distinguish between retina affected and healthy patients. Thus, only diseased population will be referred to experts.

From the beginning itself, Diabetic retinopathy shows distinguishable lesions (abnormalities) in the retina at every stage of disease progression. Every lesion shows certain explicit attributes which can be used by a computer-based algorithm for the detection

process. Detection of these lesions gives important information for disease growth.

The very first lesion that can be clinically recognized by an expert is Microaneurysm (MA). MAs are small bulges occurring in the walls of retinal capillaries. The bulges may burst spreading blood in the nearby retinal region causing another DR lesion called hemorrhage. MAs are circular in structure with an approximate diameter of 10 μm to 125 μm. They appear as dark red dots in color fundus image. Detection of MA helps in early detection of DR.

Many efforts have been made for the detection of MAs, the key evidence of the presence of Diabetic Retinopathy. In the year 1996, T. Spencer et. al., [1] put forward a methodology to identify MAs based on matched filter and mathematical morphology. Many authors took reference of his work and tried to extend the work by adding different classification steps. In the year 2005, M. Niemeijer et. al., [2] proposed a new approach by combining two strategies of Spencer et. al., and Frame et. al., along with the nearest neighbor classifier to detect MA candidates from fundus images. In the Year 2008, Gwenole Quellec et. al., [3] presented an approach that includes wavelet transform for detection process for MA. The Year 2009, A. Mizutani et. al., [4] suggested the use of double ring filter for candidate MA detection. A filter is prepared to have inner ring of diameter 5 pixels and outer ring of 13 pixels which is used for the candidate detection process. Artificial Neural Network classifier is used for classifying candidate objects.

In the year 2010, Zhang et. al., [5] put forward a method where multi-scale correlation coefficients. The authors make use of a correlation coefficient to find the similarity between the Gaussian function and the gray level distribution of MA. If the similarity is high, then correlation measure is high and vice versa. Since MAs have different sizes, the Gaussian function also uses multiple sigma values and multi-scale correlation coefficients are required.

In the year 2013, Lazar and Hajdu [6] put forward an MA detection method based on intensity profiles of MA candidates. A feature set computed from intensity profiles and is used to train a classifier. The trained classifier model then classifies true MAs from false candidates. Lama Seoud [7], 2016 contributed in finding a set of dynamic shape features for detection of MAs.

2. METHOD DESCRIPTION

The method presented in the paper presents an accurate approach for detection of MAs present in the input fundus images. The operations involved in processing are described in Figure 1. The image is processed in three stages. First one is the pre-processing stage. In this stage, the basic contrast enhancement operations are performed for conditioning the input image so that the targeted lesions should be highlighted on the background. Next stage is the candidate extraction stage. Here, all the components which are likely to be our targeted lesion are extracted from pre-processed image. The Last stage involves classification. A Naive Bayes classifier is used for classifying true lesions from false ones.

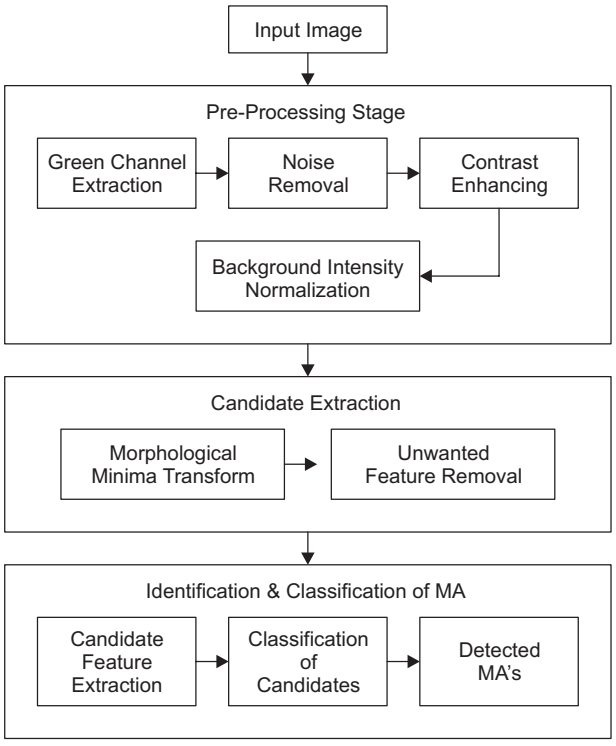

Figure 1: Flow Diagram

A. Preprocessing Stage

This stage is added to highlight our targeted lesion, Microaneurysm, from the overall background image.

The input image is the RGB image of the retina captured by a fundus camera. MAs are clearly visible in the green plane of the retinal image since it has the highest contrast among the remaining two planes [8]. MAs can be seen as small dark round dots in the green plane image. Though this plane contains more information of MAs, certain noise reduction as well as contrast enhancing operations will add more visibility to them.

Since MAs appear as dark dots in the green plane image, they resemble a pepper noise in some amount. Therefore, a median filter is used for removing the pepper noise from green plane image. As a measure for contrast enhancement, we use a contrast limited adaptive histogram equalization (CLAHE) technique to brighten the overall image.

Though histogram equalization is performed, some intensity variations in the background can be observed clearly. These intensity variations may add false candidate detections as our candidate extraction process is based on intensity feature. To normalize these variations an averaging filter with a large kernel of 35x35 is applied on the CLAHE image. This filtered image actually estimates the intensity of the background which can be subtracted from original image to produce background intensity normalized image with highlighted MAs. Figure 2 shows input image along with final pre-processed image. The Micro aneurysms are indicated in both the images in black and yellow ellipses.

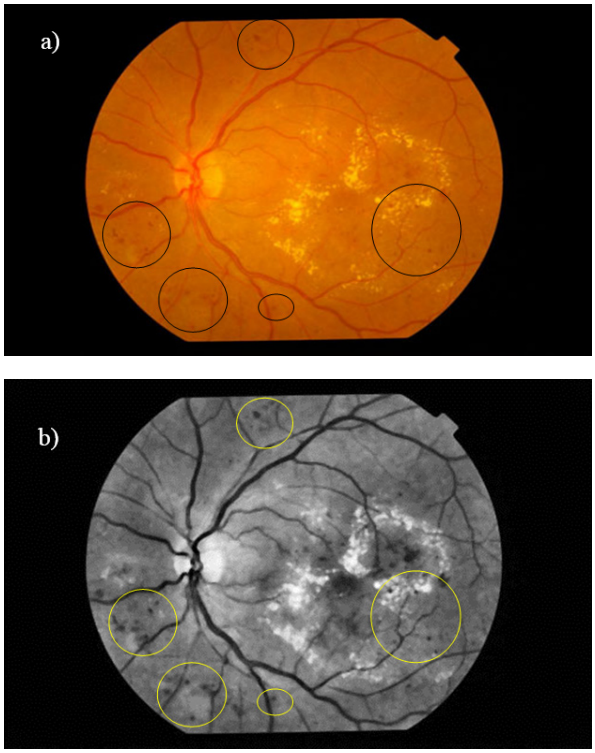

Figure 2: (a) Input Image, (b) Final Pre-processed Image.

B. Candidate Extraction Stage

Candidate extraction stage segments all the components from the pre-processed image which are likely to be Microaneurysms. For candidate extraction purpose we utilize the basic intensity feature of microaneurysms. As shown in Figure 2, the microaneurysms are small dark circular dots. They are the minimum intensity components than all the other components of the image. In order to segment these dark dots, a morphological transform called extended minima transform is applied [9].

Extended minima transform is obtained by finding regional minima of h-minima transform of a gray scale image. The extreme intensity candidates in an image can be filtered out with the help of this *h*-minima function. It extracts all the minima's in an image based on contrast criteria provided. Given a threshold value *h,* the extended minima suppress all the minima's lower than *h.* Mathematically it is defined as reconstruction by erosion ($R^{\in}$) of an image I by image I + *h* when value of *h* is given.

$$h\_\min = R_I^{\in}(I + h) \quad \text{(a)}$$

For finding extended minima, we have to find the regional minima of *h*_min image. A regional minimum extracts all the connected components from an image with a constant intensity value and surrounded by the boundary pixels having greater intensity than the constant intensity of connected component. Mathematically, the extended minima of final pre-processed image is written as follows:

$$I\_\text{ext min} = \{\text{Ext min}(I_p)\}\,|_{d=0.04} \quad (2)$$

where, I_p is the final pre-processed image with its gray level values transformed in the range of 0 to 1. $d = 0.004$ is threshold chosen experimentally which includes maximum MAs at the output.

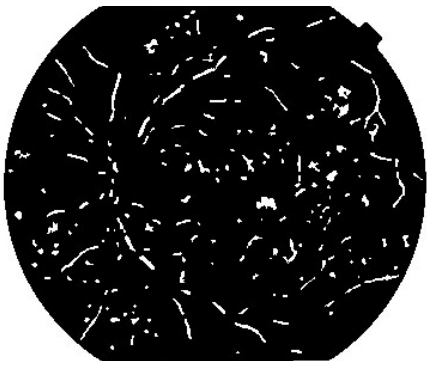

Figure 3: Extended Minima of Input Image

C. Unwanted Component Removal

There are two Components in the retinal image that adds false detection at the output and reduce the accuracy. One is the retinal vasculature structure. As shown in Figure 2, the retinal vascular structure has the same intensity as that of the microaneurysms. At the output of extended minima transform (Figure 3), some vessel parts are also extracted along with the true MAs. Some of the vessel leftovers are in the form of small dots and can't be distinguished from true MAs. Since MAs are swellings occurring on the capillary walls, they can't occur on main vessel structure of the retina. We use vessel segmentation method described in [10].

For segmenting the vessels, we slide a window of size $w = 15$ pixels on every pixel of the input image and the average intensity of the window is computed as I_{avg}. Then 12 lines with different orientations angles are passed by taking the targeted pixel at the center. The angles vary from 0 to 180 with 15° angular difference. The length of the lines is also varied from 1 to w.

The average intensity of the pixels lying along each line is computed. The line with maximum intensity is denoted as I_{max}. The values I_{avg} and I_{max} are used to compute line response as $L_r = I_{max} - I_{avg}$. If the response is large it means pixel is a part of vessel otherwise, it is considered as background pixel. The segmented vascular structure is shown in Figure 4(a).

Because of diabetes, excess pressure is exerted on retinal vessels due to which they leak some fluids in the surrounding region of the retina. The leaked fluids appear as yellowish particles in the retinal image are called as exudates. Exudates are another lesion found in diabetic retinopathy. They occur in clusters and lie very close to one another. Sometimes low intensity islands get formed in between the bright intensity exudate clusters. They can be considered as false detection for MAs.

To reduce false detections, these bright lesions are detected and masked on extended minima. we detect by the method these lesions as described in [11]. Exudates also segmented by using the morphological operations. Figure 4(b) shows segmented exudates.

The two unwanted components of retinal image are subtracted from extended minima image (Figure 5(a). From the resulting image, we select our candidate components based on an area criterion. Since MAs are circular small dots with diameter ranging from 10 μm to 125 μm, we select all the candidates with area of 15 pixels and less as our candidate MAs. (Figure 5(b).

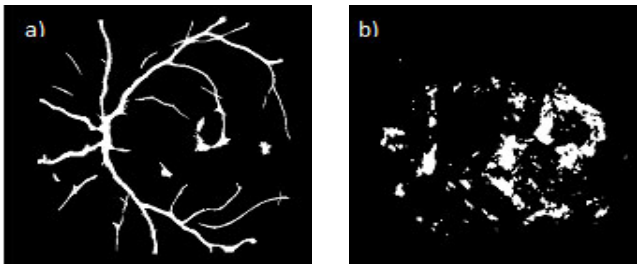

Figure 4: (a) Retinal Vessel Structure (b) Exudates

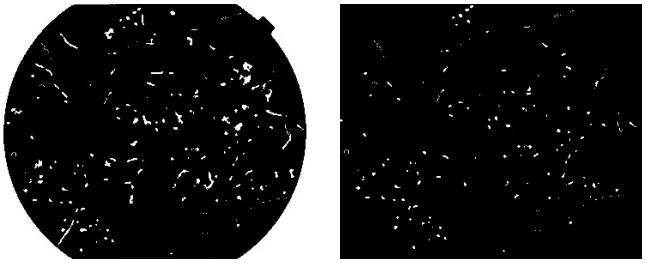

Figure 5: Candidate Extraction: (a) unwanted components subtraction (b) Final candidate components

D. Feature Selection and Classification

A feature set is computed for training a Naive Bayes classifier. In total, a set of 10 features is used. The feature set includes shape features, intensity features, and statistical features.

1. **Shape Features:**
    - Area of candidate
    - Circularity of candidate

- Perimeter of candidate
- Eccentricity of candidate
- Ratio of Major axis to Minor axis of candidate

2. Intensity Features
   - Gradient approximation by Sobel operator
   - Candidate's mean intensity in green plane
   - Candidate's mean intensity in hue plane
   - Candidate's mean intensity in pre-processed image
3. Statistical Feature
   - Standard deviation of candidate

Above features are computed and a feature matrix is formed which is given as an input to a Naive Bayes classifier. A Naive Bayes classifier belongs to the family of probabilistic classifiers that works on Byes decision theory. Bayesian classifiers are applied for automated medical diagnostic tests. The classifier assumes that the features used to describe the objects are independent of one another provided that the class value is known.

The classifier model classifies the unknown object to most probable class depending upon the maximum a posteriori (MAP) decision rule. Consider $f = (f_1, f_2, ..., f_n)$ is a set of finite features required to describe the object. Suppose we have two different classes C_1 and C_2. The model classifies 'f' to a particular class if a posteriori probability of that class is more than a posteriori probability of other class. Following steps gives the overall idea of the classification performed by a Naive Bayes classifier.

1. Compute the a-priory probabilities of each class $P(C_i)$ from training data.
2. Compute the feature vector $f = (f_1, f_2, ..., f_n)$ of unknown object.
3. Suppose we have m different classes labelled $C_1, C_2, ..., C_m$.
4. The classifier labels the unknown object to a class C_i if $P(C_i|f) > P(C_j|f)$ for all $1 \le j \le m$ and $j \ne i$.
5. Combining the above decision rule with a-priori probabilities we get,
$$P(C_i|f) = P(f/C_i) \times P(C_i)/P(f)$$
6. Maximizing $P(f/C_i) \times P(C_i)$ since the denominator $P(f)$ is constant for each class.
7. We have f as a vector with more than one feature, therefore, final expression is given by
$$P(f|C_i) = \prod_{k=1}^{n} P(f_k|C_i)$$
8. According to above theory, the final class label is given as
$$\text{label} = \arg\max(P(C_i) \times P(f|C_i))$$

The Naive Bayes classifier ensures minimum error rate for every classification performed. The classification performed in the project is candidate based. All the 10 features are computed for each candidate obtained at the output of candidate extraction stage. These features and pre-defined class labels are used while training the classifier. The project involves a simple binary classification problem with two classes.

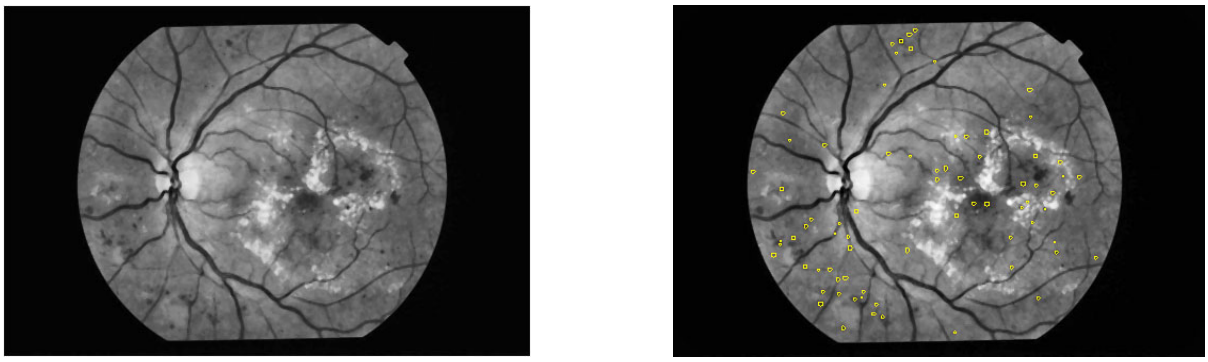

Figure 6: (a) Preprocessed Image (b) Detected MAs superimposed on Preprocessed Image

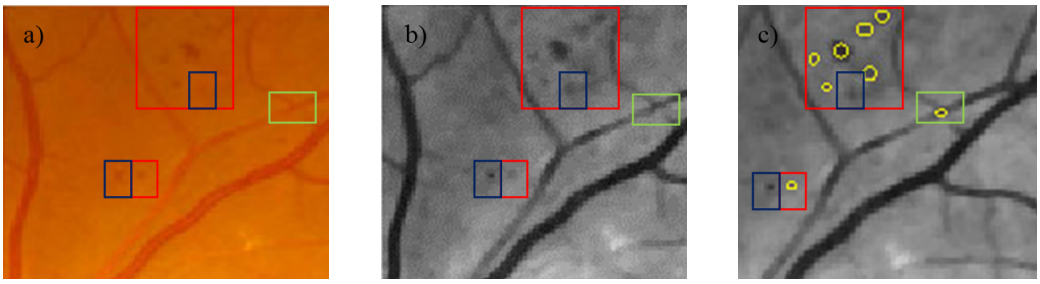

Figure 7: Image showing examples of TP, FP, FN in: (a) Original Image, (b) Preprocessed Image, (c) Classifier Output

Class label of 0 is assigned to the non-MA candidate whereas class label of 1 is assigned to the MA candidate. Total 835 MA candidates and 471 non-MA candidates have been used for training a classifier to test 15 images. The candidates classified as MAs by the classifier are shown in Figure 6(b).

3. RESULTS AND DISCUSSIONS

The algorithm described is trained and tested on an image set collected from a local eye hospital. From a set of 46 images, 31 images are used for training and 15 images are used for testing the Bayes classifier.

The algorithm was developed with the help of MATLAB software. First, the green plane of an RGB input image is extracted. Some contrast enhancement operations are carried out on the green plane image so that intensity variation should not affect the further process. A morphological minima transform is used to extract all the possible targeted lesions from pre-processed image. Subtracting the unnecessary features from extended minima image and selecting the components based on area criteria gives the final set of candidates which are likely to be microaneurysms. From these candidates, true microaneurysms are classified by a Naive Bayes classifier. The algorithm is described in detail in above sections.

From the output of classifier, four counts are computed for every image. True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN).

- True Positive: The count of true MA candidates classified as MAs by classifier
- True Negative: The count of non-MA candidates classified as non-MA by classifier
- False Positive: The count of non-MA candidates classified as MA by classifier
- False Negative: The count of MA candidates classified as non-MA by classifier

Figure 7 shows the examples of TP, FP and FN bounded by different coloured rectangles for each one. Figure 7(b) and Figure 7(c) replicate the rectangles at the same positions as in original image (Figure 7(a)). It can be observed that the visibility of MAs is more in pre-processed image than in original image. The red coloured rectangle represents the true positives i.e. MA candidates are correctly recognised in all the three images. The green coloured rectangle shows the example of a false positive. The candidate detected in the classifier output image (Figure 7(c)) is actually a vessel crossing point but wrongly classified as MA by classifier. Blue coloured rectangle shows FN i.e. The MA candidates Blue coloured rectangle shows FN i.e. The MA candidates which are missed in the final classifier output.

TN are the candidates which are non-MAs and correctly classified as non-MAs. This count is obtained by subtracting the counts of TP, FP and FN from total number of candidates detected.

From these four counts, three parameters were computed to judge the performance of the algorithm that are sensitivity (SN), specificity (SP) and accuracy (AC). Sensitivity depicts the ability of an algorithm to recognise the diseased candidates correctly. Specificity depicts the ability of algorithm to recognise healthy candidates correctly. Accuracy depicts the overall correct recognitions from total results. Mathematically, the sensitivity, the specificity and the accuracy, can be formulated as follows:

$$\text{Sensitivity} = TP/(TP + FN)$$

$$\text{Specificity} = TN/(TN + FP)$$

$$\text{Accuracy} = (TP + TN)/\text{Total Candidates}$$

In order to interpret the performance of a two-class classifier, a graphical plot called receiver operating characteristic (ROC) is studied. The ROC curve is obtained by plotting the sensitivity against the false positive rate(FPR) computed from the classifier output. The TPR is considered as the probability of correct detection i.e. sensitivity. The FPR is considered as the probability of false detection and computed as (1- specificity). ROC curve is used as a tool to test the classifier quality. Fig. 8 shows the ROC curve plotted for average TPR and FPR.

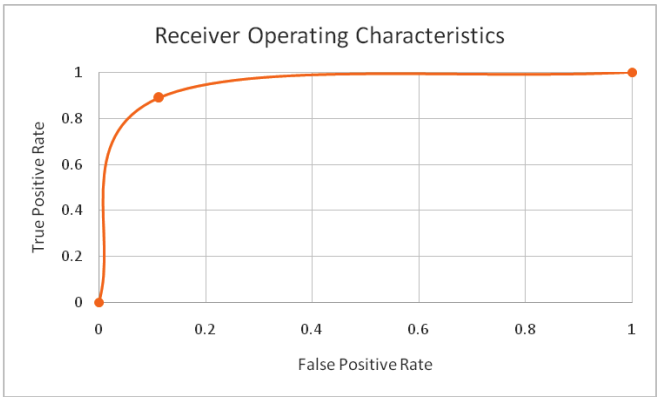

Figure 8: ROC curve for average TPR and FPR

The algorithm has achieved the average sensitivity of 88.83%, specificity of 88.67% and accuracy of 89.33%. The performance of this algorithm is compared with the performance of other authors (Table 1).

Table 1
Performance comparison

Author Name	*Method*	*Sensitivity*
A. Mizutani et. al., [4]	Double ring filter is used for MA candidate detect	65% with 27 false positives per image.
Bob Zhang et. al., [5]	Correlation coefficient is used for candidate extraction	71.3%
Abhir bhalerao et. al., [12]	LoG filters along with circular symmetry operator gives candidate MA set and Eigen values give true MAs	82.6%
Proposed Method	Morphological operations combined with classifier stage	88.83%

4. CONCLUSION

The disease diabetes is thriving amongst the huge population very rapidly. The people who suffer from diabetes for more than 10 years develop the sight-threatening Diabetic retinopathy. These patients should regularly consult with DR experts to prevent the DR progression till the vision threatening stage. In this scenario, the DR expert to the patient ratio is very low. This may result in increased workload to the DR experts and delayed treatments of the patients.

The paper tries to contribute a little effort to reduce the workload of DR experts by automating the lesion recognition process. The algorithm accurately detects the targeted lesion with the 88.83% sensitivity. Since MAs are the first lesions to be clinically recognised by DR experts, their detection leads to the early detection of the DR itself.

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