

# Microaneurysm Detection Analysis in Fundus Images

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**Abstract-** An eye condition known as diabetic retinopathy can cause vision loss. Non-proliferative diabetic retinopathy is the early stage of the disease. For the health of patients and clinical diagnosis, non-proliferative diabetic retinopathy must be automatically detected. Microaneurysms happen as the first sign of DR. For DR screening, accurate and reliable microaneurysm detection in fundus imaging is crucial. The inspection time is cut down and accuracy is maintained thanks to automatic detection. In order to identify microaneurysms in retinal fundus images, this research analyses various retinal circumstances, methodologies, and algorithms. We looked at many methods, and we found that algorithms work well to find retinal haemorrhage.

**Index Terms -** Diabetic retinopathy, microaneurysms, Classification, Preprocessing; DR, Segmentation.

## I. INTRODUCTION

Important components of the eye include the retina. When a human's vision is developing, it is extremely crucial. Figure 1 depicts the structure of the retina. On the inside side of the eye's back, the retina is a spherical anatomical structure. The rods and cones are the photoreceptor cells that are involved in the extraction of visual information. The vascular system that is visible from the outside provides blood supply for the retina. The fovea, which is responsible for crisp vision, is located in the macula, which is a darker, circular structure near the centre of the retina. When the optic nerve fibres leave the eye, they exit through the optic disc and the optic cup, which is a brilliant oval region. When the optic nerve fibres exit the eye, the optic disc and the optic cup are two bright oval spots that provide details on the anatomy of the eye [1,3].

Diabetic retinopathy, an eye condition, can be diagnosed in people with diabetes. It occurs when excessive blood sugar destroys the retina's blood vessels. These blood arteries have a tendency to enlarge and leak, which prevents blood flow. In the retina, aberrant new blood vessels can occasionally form. The unique retinal structure and these circumstances restrict the potential visibility of abnormalities brought on by different disorders. Blindness or loss of eyesight can result from any harm.

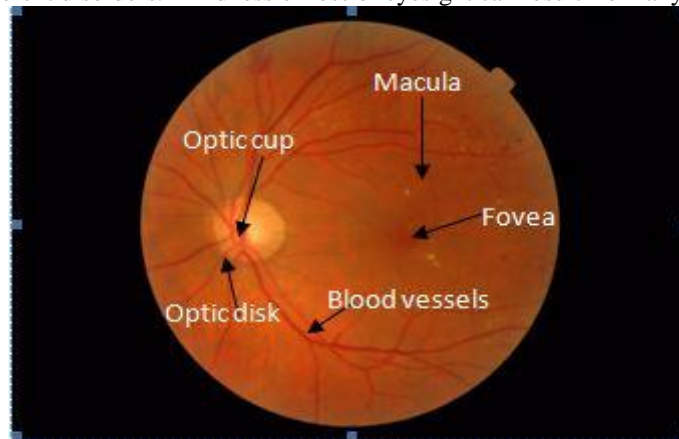


Fig 1: Retinal fundus image with anatomic parts

The patient is typically unaware of the presence of DR in the early stages; but, later on, patients may feel floaters, distorted or blurred vision, etc. Non-proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) are the two main classifications. The earliest stage of diabetic retinopathy is known as NPDR. It features problems like Retinal haemorrhages, which are microscopic blood spots that seep into the retina, Hard exudates, which are deposits of fat from the blood that has leaked into the retina, and Micro-aneurysms, which are little bulges in the retina's blood vessels.

The earliest clinical sign of DR, Micro aneurysms, which resemble tiny, red dots in the retina's superficial layer, are red lesions and haemorrhages. These are symptoms of NPDR. Dot and blot HMs are formed by MAs that burst in the retina's deep layers and resemble MAs when they are small.

On retinal imaging, the lesions are seen as bloody spots. In the early stages, known as mild non proliferative DR, micro-aneurysms (MA) are red lesions seen, while in moderate non proliferative DR, bright lesions such exudates and cotton wool patches are seen. When the blood vessels in the retina are clogged and there is no blood flow, proliferative DR develops.

When rating the severity of DR, these abnormalities are regarded as important facts. Hence, these symptoms aid in the diagnosis of this illness. Automatic retinal image analysis has become crucial for ophthalmologists to make an early diagnosis. The first sign of DR is the appearance of microaneurysms.

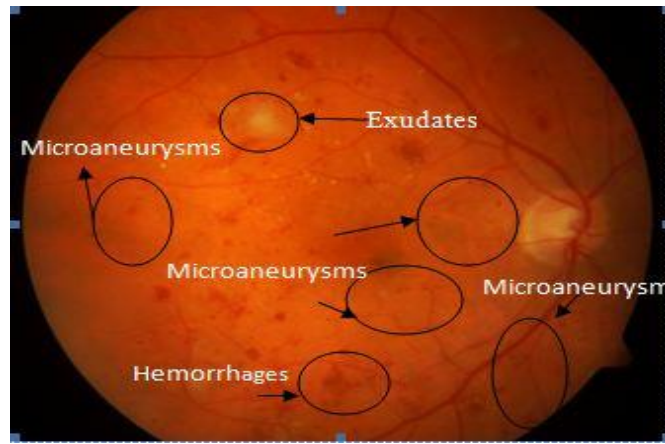


Fig 2: Retinal fundus image containing hemorrhage

Fig. 2 displays the microaneurysms in various sizes and forms. Microaneurysms are vascular leakage-related eye conditions that typically present as tiny red dots inside the eye that are encircled by yellow bands. Microaneurysms exhibit no additional symptoms and have no impact on vision. This study examines various methods for finding microaneurysms.

**II. LITERATURE SURVEY**

A neural network strategy was put forth by Kamel et al. [18] for the automatic detection of micro aneurysms in retinal angiograms. There are many sections or windows in the image. The Learning Vector Quantization technique is used to divide the input patterns into the required classes.

A microaneurysm detection technique using a region-growing algorithm in colour fundus images was put out by Streeter et al. [10]. The blood vessels are removed during preprocessing. Finally, using a candidate seed image, the thresholding and region-growing algorithm is applied. The features are extracted after region expansion.

A microaneurysm detection system was modelled by Kedir et al.[12] to locate blobs or interest spots in a retinal picture. For MA detection, an automatic local-scale selection method was developed. Several scale-adapted region descriptors were generated to characterise the region containing the blob. A method of semi-supervised learning was created.

On each contender, Frame et al. [9] compiled a collection of attributes such shape features and pixel-intensity features. Then, using these traits, the classifier is used to categorise each candidate as a microaneurysm or a non-microaneurysm.

By employing sub-bands of the wavelet processed images and matching them with a lesion template, Quellec et al. [7] established a digitalized technique to detect MAs. The procedure of a genetic algorithm was used for optimization. Powell's directive for the successful detection of MAs came next. A professional evaluated 120 retinal images, analysing the best wavelet and comparing it to other wavelets that are currently in use.

**III. DETECTION OF MICRO ANEURYSMS**

The majority of processing techniques for detecting retinal haemorrhages follow the order of steps depicted in Fig 3. The dataset collection stage is the most crucial one in order to do subsequent procedures. The following processes are carried out after gathering the dataset. The preprocessing approach is the first one employed when using image processing techniques. The images or data are prepared for actual processing after preparation is complete. The next step is the segmentation of some features, which could result in inaccurate results being calculated. Following segmentation, classification is completed.

**2.1. Image Dataset**

Any research project begins with gathering a significant amount of data. Only then can a researcher effectively conduct their investigation and compute the outcomes. The imaging data collection is necessary to accurately diagnose the micro aneurysms.

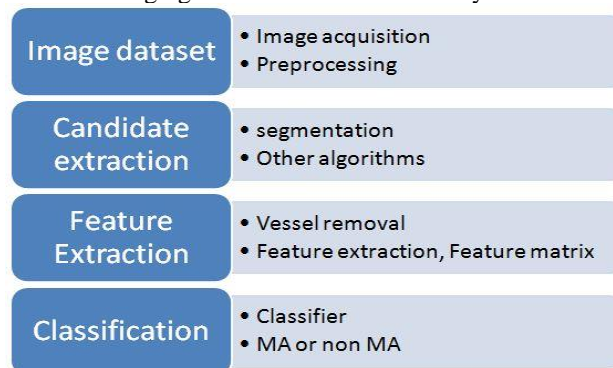


Fig 3: Steps to detect retinal hemorrhage using Fundus Images

There are several databases that offer vessel ground truth photos that accurately pinpoint each vessel pixel's location. Researchers can construct their algorithms and compare their performances using the criterion using those databases.

Images enabling the detection of micro-aneurysms are readily available in the Diaretdb1 database. Both retinal colour images and retinal blood vessel ground truth images can be found in the databases STARE [13]. Retinal colour images are available in the other databases DiaRetDB1 V2.1 [15] and ROC [14], although without labels. With the aid of these databases, algorithms can be used to determine the likelihood of finding retinal microaneurysms.

## 2.2 Preprocessing

To enhance the quality of the captured image, image preprocessing activities are necessary. Due to interference and other factors, noise frequently degrades medical imaging. There are so many photographs that have noise, brightness, or blurry effects. So, in order to obtain correct findings and prevent misclassification, it became crucial to eliminate this noise and prepare the images for the subsequent operation.

Image enhancement is the process of raising an image's quality in order to increase how much information can be seen in it. Mean or Median filters can be used to eliminate the dispersion of extreme image values. Robert is an algorithm that increases the image's sharpness by extracting edges. Methods for enhancing contrast include histogram equalisation, linear contrast modifications, and nonlinear contrast adjustments. With the purpose of eradicating [27] vignetting effects from the image, [21], [11] employed lighting equalisation.

The colour of the retinal fundus picture changes as a result of flash. The illumination equalisation was utilised by [21]. They applied the hue saturation value (HSV) system for brightness correction. To enhance the contrast in [21], they used the Contrast Restricted Adaptive Histogram Equalization method. They employed contrast-limited adaptive histogram equalisation in publication [5]. (CLAHE). To improve the contrast between the background and the component, they combined it with various enhancement methods.

## 2.3 Segmentation

The intention of picture segmentation is to convert a complex image representation into a more straightforward one. The process of image segmentation is used to identify boundaries and objects in images. Each pixel in a certain area of an image shares the same characteristics or properties, such as colour, intensity, or texture. In terms of qualities, the closer regions differ greatly from each other. To merge pixels into image regions, segmentation of the image is performed.

A technique for the early detection of DR was put forth by M. Usman Akram et al. [5]. For the purpose of using filter banks to detect MAs early, a three-stage system has been developed. The system retrieves all potential candidate regions where MAs are offered in the first stage step.

A method to extract a subset to separate the red lesions from the backdrop of the image was suggested by Garca et al. [22]. The final segmentation of retinal lesions was obtained using an MLP (Multilayer Perceptron) classifier.

Several segmentation techniques are employed in the detection of retinal haemorrhages. They added splats to the colour picture in [2]. Also, they classified the photos as being normal or having haemorrhages using the splat features.

The structural structures of the eye, such as the optic disc, blood vessels, macula, and optic nerve, among others, must be segmented out or detected during the segmentation stage, along with the lesions and other things. Misclassification of haemorrhages or lesions must be avoided at all costs. So, it is necessary to find those things before classifying them.

### 1) Blood vessel detection and removal

In order to retain accuracy, we must first identify and delete any additional anatomical objects from the retinal image, such as blood vessels. Separating the vessels from the image is what it entails. In doing that, we could run across issues like poor contrast and brightness, which can cause blood vessels to be detected wrongly, affecting the results. Before performing vessel detection and removal, the proper preprocessing procedures must be used.

There are numerous algorithms that may be used to find and recognise vessels in photos. The second option is to completely eliminate the vessels from the image, while many only identify the vessels and extract the information before processing the image further. According to one method [1] [6][7], algorithms are used to determine vessel borders by applying an edge detection operator. Extracting data from properties such vessel widths, centre points, locations, orientation, and boundaries, among others, is another method for detecting information about vessels. Once we have this knowledge, it will be simple to identify the blood vessels in the image. Several techniques, including matching filters, thresholding [21], morphological procedures, etc., are used to eliminate the vessels. The vessel from the original photograph, Fig. 4, is depicted in Fig. 5.

### 2) Optic disc segmentation

The automatic diagnosis of the retinal haemorrhage in fundus images heavily relies on the placement of the macula, fovea, optic disc, and optic cup in retinal imaging. The retinal vasculature enters and exits the eye at the optic disc region of the retina. The optic disc can be mistakenly labelled as abnormal by detecting algorithms or approaches because its appearance is distinct from the texture of the retina.

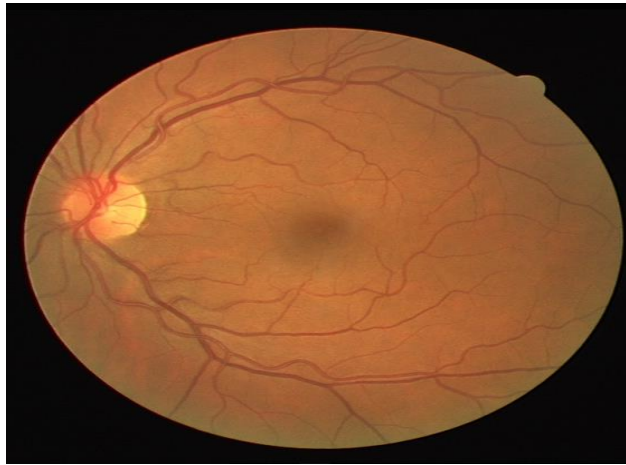


Fig 4: Original image with the retinal blood vessels



Fig 5: macula detected using Fig 4

The algorithm was applied by to find the optic disc and fovea. A set of a thousand photographs were used, many of which show various retinal abnormalities like exudates, cotton wool, and micro-aneurysms [7].

The green plane of the colour image is used in the procedure for detecting the optic disc and fovea. The green plane of the image is blurred using a Gaussian filter to remove low frequency gradients from the image.

### 3) Optic nerve detection

Another crucial component of the retina is the optic nerve, which transmits information from the eye to the brain. It receives all visual information from the retina and transmits it to the posterior surface of the eye. We can quickly spot these nerves in a normal image, but photos with lesions make the task more challenging. These lesions' brightness crosses over with the nerve's brightness.

Based on the transformation of gradient edges into a Hough space, nerve detection is performed. The optic nerve can be located using a method described in as a starting point for tracking-based segmentation of blood vessels [24]. To find the optic nerve in [R19], they used the fuzzy convergence method.

### 4) Macula and fovea detection

The greater portion of the optic disc and the fovea must both be visible in the image for the macula and fovea to be effectively detected. They presented a method in [7] to identify the fovea from a retinal picture.

In order to prevent categorization errors, the retina's structure can be simply removed or detected in this way. After that, we must use the procedures to accurately identify any lesions or haemorrhage present in the image. They created a splat on a retinal colour image in [2]. After identifying the arteries and the optic disc, they used the watershed method to identify any haemorrhage that was still present.

## 2.4. Feature extraction

The next stage is to extract the features of the segmented haemorrhage or lesion after using all the previously necessary approaches and segmenting the area of interest. To detect the condition and train the algorithm, many features are retrieved from the segmented image. We must choose features that can lower the dimensionality of the feature space when combining them [2]. The filter technique and the wrapper approach are the two main methods for feature selection that were provided in [1] and [2]. While the wrapper approach combines several features, the filter approach is quicker.

Several parameters, including texture, filters, area, and ratio, are retrieved and can be applied to further processing in order to identify retinal haemorrhage. The grey level co-occurrence matrix [2] and two gray-level difference statistics were utilised in [10]. They



extracted Tamura [2], gray-level co-occurrence of the matrix, vessel diameter, distance of the optic disc, distance from the centroid of the fovea, and other information from [21].

In previous research work author employed a colour image, processed the colour image, and extracted information such as area, solidity, extent, orientation values of the splat and RGB colour channel, among others [2].

## 2.5. Classification

The next step is to use or construct the classification algorithm after the features have been extracted. This classification uses the feature matrix as the input, trains the algorithm using the features collected, and then, during testing, can distinguish between an image that is normal and one that contains a lesion or haemorrhage. To ensure that our algorithm produces correct results, it is crucial to employ a good classification algorithm.

They applied a feed-forward neural network in [3]. Because of its predictive strength, computational efficiency, and ease of interpretation, the Support Vector Machine (SVM) algorithm is used in [21], and they obtained an AUC of 0.89 and an accuracy of 88.

Results for classification are computed as a percentage, ROC curve, AUC, as well as specificity and sensitivity. A binary classification test's performance is statistically measured by sensitivity and specificity. In biomedical imaging, these assays are frequently employed. The proportion of correctly detected positives is measured by sensitivity, whereas the proportion of correctly identified negatives is measured by specificity.

## IV. CONCLUSION

In this work, we examined the methodologies and procedures for detecting retinal microaneurysms. Researchers have created many automatic detection systems using these strategies. This study provides a step-by-step guide for conducting research on an algorithm for the detection of retinal microaneurysms. We must be extremely careful when developing the automated microaneurysm identification because any result misclassification could result in complete sight loss. This study lists a number of issues that could arise at each stage, from preprocessing to classification.

There are numerous difficulties in automatically finding microaneurysms. Due to background noise, contrast, and blood vessel similarity, among other factors, it might be challenging to distinguish a microaneurysm from its surroundings. Anatomical components of the retina, such as the blood vessels, fovea, and, can lead to a misclassification of this microaneurysm identification. Hemorrhages can vary in size, develop in different places or next to blood arteries, and frequently they are so little that they might be mistaken for noise, microaneurysms, or they may be removed while segmenting the retinal structures.

The most crucial detection occurs when blood vessels are removed and they are next to or covered by microaneurysms or lesions. So, while using automated detection methods to categorise the situations, we must use the utmost caution. This essay provides a general overview of words relevant to diabetic retinopathy. So, it aids in technique development to have a better understanding.

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