DETECTION OF DIABETIC RETINOPATHY USING MINIMUM MEAN ABSOLUTE DEVIATION MODEL AND SUPPORT VECTOR MACHINE

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ABSTRACT:
This paper presents an automated system to analyze the retinal fundus image for the presence of diabetic retinopathy, which is one of the diseases that cause blindness if left unnoticed at their earliest stage. Diabetic retinopathy is asymptomatic at their initial stages hence it is very difficult to identify them manually. So an automated system is designed, in which a retinal fundus image is fed to the system where it is subjected to various processes for the identification of diabetic retinopathy with high accuracy. Initially the image is subjected to pre-processing where the noises and other photographic artifacts are removed. Next, image segmentation is carried out to segment the area of interest. Although many segmentation algorithms have been designed earlier new algorithms are being proposed every day to improve the accuracy of segmentation and to decrease the computation time. MMAD model is used in this work to segment the lesion/exudates from the retinal images. In this model the 2D histogram of the preprocessed image is converted to the 1D histogram through diagonal projection and that is subject to the segmentation which produces the accurate result and the computational time is greatly reduced when compared to various other algorithms. The final stage in this system is lesion classification where the most important properties of the lesion are taken and given to the system. Support vector machine classifier is used to classify the lesion with higher accuracy and the performance of the proposed work is analysed with existing algorithms.

KEYWORDS: Fundus images, Histogram equalization Minimum Mean Absolute Deviation(MMAD), Support Vector Machine.

1. INTRODUCTION
Diabetes is a disease which occurs when the pancreas fail to secrete enough insulin or the body unable to process it properly. As diabetes progresses, the disease slowly affects the circulatory system including the retina of the human eye and as a result of long term accumulated damage to blood vessels leads to declining the vision of patient which is termed as diabetic retinopathy [2]. Diabetic Retinopathy is an eye disease that can lead to partial or even complete loss of visual capacity, if left undiagnosed at the initial stage [16]. Retinal lesions associated with the disease are used to evaluate different stages and the severity of the disease. According to WHO (World Health Organization) there will be 79 million people with diabetes by 2030, making the Indian Diabetic capital of the world. Retinal images acquired through the fundus camera with back-mounted digital camera provides useful information about the consequence, the nature and status of the effect of diabetes on the eye. These images assist ophthalmologist to evaluate patients in order to plan different forms of management and monitor the progress more efficiently. If left untreated then Diabetic Retinopathy (DR) becomes the leading cause of blindness and visual disability [3]. The effect of diabetes on the eye causes DR (as shown in figure 1). It can damage the small blood vessels of the retina and this might lead to loss of vision. There is no preprocessing and so false photographic effects may be mistakenly graded as exudates [8].

1.1 Background diabetic retinopathy
Background diabetic retinopathy (BDR) is named appropriately because it sits in the background, not itself a danger to vision, but is instead a warning sign that serious damage may be starting. Directly above the white arrows in the picture are two small flame shaped hemorrhages with tiny micro aneurysms. Micro aneurisms are usually the earliest visible change in retinopathy seen on exam with an ophthalmoscope as scattered red spots in the retina where tiny, weakened blood vessels have ballooned out. Hard Exudates caused by proteins and lipids from the blood leaking into the retina through damaged blood vessels. They appear on the ophthalmoscope as hard white or yellow areas, sometimes in a ring like structure around leaking capillaries. Again vision is not affected unless the macula is involved.

1.2 Proliferate Diabetic Retinopathy
In this condition very small blood vessels grow from the surface of the retina. The retina is the film at the back of your eye, and the tiny blood vessels are capillaries. These growing blood vessels are very delicate and bleed easily. Without laser treatment, the bleeding cause’s scar tissue that starts to shrink and pull the retina off and the eye becomes blind. Laser treatment prevents blindness, but often some vision is lost.

1.3 Severe Diabetic Retinopathy
Diabetic eye disease refers to a group of eye problems that people with diabetes may face as a complication of diabetes. All can cause severe vision loss or even blindness in some people with diabetic retinopathy, blood vessels may swell and leak fluid. In other people, abnormal new blood vessels grow on the surface of the retina. The retina is the light-sensitive tissue at the back of the eye. A healthy retina is necessary for good vision. If you have diabetic retinopathy, at first you may not notice changes to your vision. But over time, diabetic retinopathy can get worse and cause vision loss. This Diabetic retinopathy usually affects both eyes.
2. RELATED PROBLEMS IN DIABETIC RETINO Pathy
Existing methods [14] mostly based on other eye disorders like exudates [1] and glaucoma and didn’t provide more details on the MA. It is a stepwise screening process and takes a more time. Due to more time consuming in analysis of the problem, it may effect in the diagnosis of disease and further treatment process. In order to ensure the detection of DR in an automated manner a well trained ophthalmologist is needed for screening purpose. Walter et al model is based on the extraction of candidate accomplished by grayscale diameter closing. This method aims to find all sufficient small dark patterns on the green channel. Finally, double thresholding is applied. Spencer et al analysis is based on the input fundus image, the vascular map is extracted by applying twelve morphological top hat transformations with twelve rotating linear structured elements. Laser et al. Analysis is based on pixel wise cross section profiles with multiple orientations. Small hemorrhages are regular in shape and many systems have been developed to detect them [4]–[6]. A method to enhance exudates using fuzzy morphology is proposed in [4] where, a color fundus image is converted to grayscale image first, followed by a fuzzy morphological closing operation to enhance the boundaries of exudates. In [12], the authors considered an additional pixel wise classification based candidate extraction method, and merged the output. Detection of bright or red lesions also relies heavily on color [15] and thus some color normalization is needed [5], [8]. Other approaches are based on the application of morphological operations to detect the contours of exudates [7], fuzzy c-means clustering candidates [8], [10].
This proposed work focuses on the problems described above and to overcome it by designing an automated algorithm to run on the input image from the database collected by the fundus camera and process it for the detection of Micro aneurysms.

3. AN OVERVIEW OF PROPOSED MODEL
This proposed work is based on an automated method in DR detection. It lessens the work of an ophthalmologist and produce immediate result because of applying the digital image processing of the retinal image on a computer based system. Since it is an automated process and it has the ability to consume less time and enable more data to process in small interval of time rather than going through the stepwise screening process of an ophthalmologist.
The proposed work involves three major domains and certain sub modules in each domain.

- Pre-Processing
- Feature Extraction
- MMAD segmentation
- Feature Classification and Diabetic Detection

![Figure 2. Overall proposal structure](image)

The objective of this proposed work is to develop an automated approach for DR lesion detection with high sensitivity and specificity in order to get more accuracy. Next thing is user interfacing method. Since it is an automated process it lessen the time consumption and in need of the user interfacing model in order to provide a user friendly approach. The overall method proposed here is to detect the exudates in the retina of an eye by an automated less time consuming process. It applies digital image processing concepts in the field of medical science.

![Figure 3. Overall proposed work steps](image)

The overall proposed structure consists of the following blocks as mentioned in Figure 2. It consists of the preprocessing stage, which includes obtaining fundus image from the gathered database, then resizing it followed by red channel conversion and inverted red channel conversions. The feature extraction block consists of removal of blood vessels followed by removal of unwanted artifacts and finally detection of candidate lesion that is required micro aneurysms. The final block is classification block which consists of a classification of lesions based on its count and ranks the severity of the disease based on the counting value. The implementation of this proposal includes the following stages in order to implement it in an automated fashion of the computer based analysis method. The proposal is to detect the presence of a lesion. In order to detect lesion the following process are involved.

3.1 Pre-processing
The pre-processing steps involve the following stages as shown in Figure 3. The aim of pre-processing is to attenuate the noise and to improve the contrast then to correct the non-uniform illumination. It also consists of color image conversion and resizing the image. Before image processing is carried out, the fundus images need to undergo pre-processing to remove non-uniform background. Nonuniform brightness and variation in the fundus images are the main reasons for non-uniformity. Therefore, the error needs to be corrected by applying contrast-limited adaptive histogram equalization to the image before applying the image processing operations. A histogram is a graph which indicates the number of times each gray level occurs in an image. In bright images, the gray levels will be clustered at the upper end of the graph. As for images that are darker, the gray levels will then be at the lower end of the graph. For a gray level that is evenly spread out in the histogram, the image is well-contrasted. Histogram
Exudates are a class of lipid lesions visible in optical retinal images, which are clinical signs of DR. Two manifestations of exudates are known: hard exudates that appear as bright yellow regions and soft exudates or cotton-wool spots, which have fuzzy appearance. Automatic detection of exudates is of interest as it can assist ophthalmologists in DR diagnosis and early treatment. The common approaches to lesion-level exudate detection follow a bottom-up strategy, beginning with pixel classification, followed by region-level classification (as shown in figure 5). Color values are used in pixel classification, since exudates pixels exhibit a limited range of color. Region-level classification has been attempted with features like edge-strength, mean intensity within the region, and contrast features [9]. The optic disk is a structure with similar color characteristics as exudates, imaged in the central views of the retina. Optic disk has been distinguished by using entropy features, or using dedicated methods like active contours.

3.2.1 Border detection of fundus image
The boundary is detected by filling up the holes and a disk shaped structuring element (SE) of radius 8 is created by morphological opening operation (erosion then dilation) as shown in Figure 5.

3.2.2 Elimination of border from edge detected image
The morphological opening using a linear structuring element oriented at a particular angle will eradicate a vessel or a part of it when the structuring element cannot be contained within the vessel. This happens when the vessel and the structuring element have orthogonal directions and the structuring element is longer than the vessel width

\[
I_{th} = 1 - \left( \text{top-hat} \right) \\
I_{th} = \sum_{\theta \in A} \text{top-hat}
\]

The morphological top-hat transformation is shown in (5a) where “ \( \text{top-hat} \) ” is the top-hat transformed image, “I” is the image to be processed, “SE” is structuring elements for morphological opening, “(a)”, and “\( \theta \)” is the angular rotation of the structuring element. If the opening along a class of linear structuring elements is considered, a sum of top-hat along each direction will brighter than the vessels regardless of their direction, provided that the length of the structuring elements is large enough to extract the vessel with the largest diameter. Therefore, the chosen structuring element is 21 pixels long 1 pixel wide and rotates at an angle spanning \([0, \pi]\) in steps of \(\pi/8\). Its size is approximately in the range of the diameter of the largest vessels in the retinal image. The sum of top-hat “Isth” is depicted in (5b), which is the summation of the top-hat transformation described in (5a). The set “A” consists of the angular orientations of structuring element and can be defined as \(\{x|0 \leq x \leq \pi \text{ and } x \mod (\pi/8) = 0\}\). The sum of the top-hat on the retinal image will enhance all vessels whatever their
direction, including small or tortuous vessels eliminating the bright zones as depicted in Fig. 2(a). The edge detected image is then subtracted from the image with boundary to obtain an image without boundary as shown in Figure 6. After that the holes or gaps are filled, resulting in exudates and other unwanted artifacts. The image with filled holes or gaps, then subtracts the image before filling holes or gaps. The resulting image, thus has exudates and other unwanted artifacts without the edge.

3.2.3 Removal of blood vessel
Blood vessel detection is important in identification of diabetic retinopathy (DR) through image processing techniques. Adaptive histogram equalization is performed to improve the contrast of the image and to correct uneven illumination on the red component of the image.

A morphological opening operation (erosion then dilation) is performed using the ball shaped structuring element (SE) to smooth the background and to highlight the blood vessels. The image is then subtracted from the adaptive histogram equalized image (CLAHE). The resulting image shows higher intensity in the foreground (blood vessels) as compared with the background in a contrast. From the subtracted image, the image is converted from grayscale to binary by performing thresholding with a value of 0.08. Median filtering is performed to remove “salt and pepper” noise as shown in Figure 7.

The edge detection canny method is then used on the blood vessels image to detect the edges [11]. This image is then subtracted from the image after boundary subtraction. The resultant image is shown in Figure 6.

3.2.4 Detection of Exudates
Finally, after filling the holes or gaps image is subtracted with the image with Exudates and unwanted artifacts to obtain the final image with only Exudates (as shown in Figure 5).

![Figure 7: a) filling the holes b) Detection of Exudates](image)

Figure 7 shows the filled holes and gaps which results in micro aneurysms and other unwanted artifacts with edge detected fundus image respectively [21]. This methodology includes the mean shift method to improve the efficiency of the results in finding the presence of exudates and helps in classifying them with high accuracy.

3.3 MMAD Segmentation
The input image is processed to obtain the gradient image and the grayscale image for constructing an improved 2-D gradient histogram. The global features are extracted as a 1-D histogram from the 2-D histogram by diagonal projection. Subsequently, the MMAD model (as shown in Figure 8) is used in the 1-D histogram to obtain the optimal results.

Without losing generality, let I denote a grayscale image with L gray levels of size M × N. The 2-D histogram is composed of two parameters of the image: one is the grayscale image, which is denoted by f(x, y), and the other is the gradient image. For the given function f(x, y), the gradient of f at the location (x, y) is defined as the 2-D column vector [18]

\[ \nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \]

Figure 8: MMAD Segmentation
For a discrete image, one of the simplest and, most commonly used methods to generate the gradient is to form the running difference of pixels along the vertical and horizontal axes of the image, which is described as follows:

\[ \nabla_x f = f(x + 1, y) - f(x - 1, y) \]
\[ \nabla_y f = f(x, y + 1) - f(x, y - 1) \]

3.4 Feature Classification and Diabetic Detection using SVM
The final step in object recognition using histogram of oriented Gradient descriptors is to feed the descriptors into some recognition system based on supervised learning [23]. The support vector machine (SVM) [20] classifier is a binary classifier which looks for an optimal hyper plane as a decision function. Once trained on images containing some particular object, the SVM classifier [15], [19] can make decisions regarding the presence of an object, such as a human, in additional test images.

Support vector machine training process is applied to analyze training data to find an optimal way to classify images into their respective classes, namely normal, Proliferative Diabetic Retinopathy (PDR) or Non-Proliferative Diabetic Retinopathy (NPDR) is a robust technique for data classification and regression. It is described in detail by Vapnik [26]. Support vector machine is used to discriminate the various categories. Classification parameters are calculated using support vector machine learning. The training process analyzes training data to find an optimal way to classify images into their respective classes. The training data should be sufficient to be statistically significant. The support vector machine learning algorithm [17] is applied to produce the classification parameters according to calculated features. The derived classification parameters are used to classify the images. The image content can be discriminated into the various categories in terms of the designed support vector classifier. To fit nonlinear curves to the data, SVM makes use of a kernel function to map the data into a different space where a hyper plane can be used to do the separation. SVM can be applied to nonlinear classification using...
nonlinear kernel functions to map the input data onto a higher dimensional feature space in which the input data can be separated with a linear classifier (Fig. 3 b). Kernel function \( F(x,y) \) represents the inner product in feature space. In this work, we have used polynomial kernel which is given by,
\[
F(x, \bar{x}) = (x \cdot \bar{x} + 1)^k
\]
(7)
Where \( x \) and \( \bar{x} \) are the training vectors, \( k \) is the kernel parameter. The size of the input training vector is 250 * 6. The output can be one of the three categories, namely normal, NPDR.

IV. RESULTS AND DISCUSSION

The proposed method for the detection of exudates is implemented in MATLAB 7.8 in order to perform image processing techniques on the input database images. The image input is obtained from the collected database [13] and then the techniques like pre-processing, feature extraction and classification is done by certain methodology based on the image processing tool-kit in MATLAB. Database collected contains 130 retinal images in the test set where 110 abnormal and 20 normal are analyzed by an ophthalmologist were used for testing the algorithms of our proposed model. The test set was not used during the development, but only once for testing the algorithms and for computing sensitivity and specificity values.

In this preprocessing stage the image is first resized to 720*576 resolution and then this image is subject to histogram equalization and then to adaptive histogram equalization that is the contrast of the image is enhanced through this process. The pre-processing stage outcomes show the original resized 720*576 image output and the histogram image outcome (as shown in Figure 9). The preprocessing is done to eliminate the false photography effects in the image to get the exact result of the eye.

In this step of the global contrast of the image, especially usable data of the image are represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast. The contrast enhanced image is done before performing canny edge detection in the fundus image. The edge is detected after performing a morphological operation with the disk shaped structuring element of radius as 5 (as shown in Figure 10).

As the earlier identification of the disease prevents the blindness the accuracy of the automated system plays an important role (as shown in figure 12). The various automated system is compared with proposed work and it produces better performance by having highest accuracy, sensitivity, specificity (as shown in Table 1).

V. CONCLUSION

The aim of this proposal is to develop a new featured algorithm to detect exudates that are associated with DR and classify them and grade. Work carried on the previous work consists of some pre-processing steps, feature extraction and classification of the retinal fundus image. The segmentation of the retinal fundus image is done using mean shift method to give a high accuracy of segmentation. But the time taken for the segmentation is more, thus increases the computational time. This work not only produces the result with higher accuracy, it also reduces the computational time. From the literature analysis a comparative study of various works is carried out in

![Figure 9: Original 720*576 resized Histogram image](image)

![Figure 10: a) Input and Detection of lesions and non lesions b) Detection of Hard exudates and Cotton wool spots c) Detection of Micro aneurysms and Hemorrhages](image)

![Figure 11 (a) Original image (b) Extracted blood vessels and (c) Detected exudates](image)

![Figure 12: Performance comparison of proposed work with existing algorithms](image)

### Table 1: Performance Comparison with various algorithms

<table>
<thead>
<tr>
<th>Automated system</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuzzy C Means</td>
<td>87.5</td>
<td>93</td>
<td>95</td>
</tr>
<tr>
<td>Thresholding Morphology</td>
<td>92.0</td>
<td>94.8</td>
<td>93</td>
</tr>
<tr>
<td>Histogram</td>
<td>89.5</td>
<td>88</td>
<td>91</td>
</tr>
<tr>
<td>Proposed System</td>
<td>97.89</td>
<td>98.68</td>
<td>98.49</td>
</tr>
</tbody>
</table>

The comparison is made with using existing approaches and current proposed work. It is clear that the proposed work has produced better performance and highest accuracy.
detecting the lesions are analyzed. The best methods generating a very good performance are chosen in this work in order to build a better automated algorithm. This analysis is done based on better sensitivity and specificity to ensure high accuracy of the disease.

VI. FUTURE WORK

Future work will address an issue of improving the sensitivity by improving the results of other tasks, such as the detection of the optic disc and blood vessels and also to localize faint and small exudates. In future, work to expand the detection system to recognize micro aneurysms and haemorrhages with very high sensitivity, there may be a problem in separating the pathologies from small vessels when seeking a very high accuracy, hence to solve that by taking them to account and train the system with more number of normal and abnormal fundus images in order to get high sensitivity and high specificity. We can detect the pathologies and subtract them from the image. If small vessels are missed during this step and are confused with micro aneurysms or haemorrhages it may be possible to combine more than one detection technique to make a final decision on the likelihood of the detected area being either a vessel or micro aneurysms or a haemorrhages. Although this method gives a very high sensitivity and specificity the future work will still more healthier in detecting them and classifying with improved algorithms and more training to the systems. The future work aims in detecting the exudates in detail and classifying them using many futures and algorithm.

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