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Extraction of Exudates from the Fundus Images A Review

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***Abstract*— The dawn of the 20th century has heralded the entry of technology into almost every sphere of our daily lives, specially healthcare. This paper deals with review of the various methods used to detect exudates present in the eye which is the indicator of diabetic retinopathy, a dreadful eye disease. The aim here is to go through the algorithms using image processing technique giving importance to highest possible accuracy. The paper concludes with an insight into the future scope of this research and how an economically viable solution can be further obtained.**

***Keywords*— Diabetes Mellitus; Diabetic Retinopathy; Exudates; Image Processing; Color Processing; Segmentation Techniques**

I. INTRODUCTION

Diabetes Mellitus is one of the most commonly found medical disorders in the world. It is a medical condition where the metabolism of carbohydrates, proteins, lipids, electrolytes and water is affected due to hormonal imbalance of insulin, resulting in variations in blood sugar levels [1]. According to a survey conducted by the World Health Organization in 2014, about 9% of people suffer from Diabetes [2]. Along with changes in the levels of blood sugar, Diabetes also affects other parts of the body such as heart, blood vessels, nerves, kidneys and eyes [3]. A very well known ophthalmological complication caused due to diabetes that can induce blindness is Diabetic Retinopathy (DR) [4]. In DR, the blood vessels that circulate nutrients in the retina rupture thus leaking the fluids that can solidify and cause blurred vision [5]. According to one of the surveys conducted in 2011, about 8.3% of the world adult population suffered from DR [6]. There are two types of DR – Non-proliferative diabetic retinopathy (NPDR) and Proliferative diabetic retinopathy (PDR) [7]. The former is the early stage of DR, where tiny lesions form on the blood vessel of retina called microanuerysms that can cause fluid leakage. The next stage is PDR, where the retina is deprived of oxygen, thus making the blood vessels fragile. This can result in accumulation of gel-like fluid at the back of the eye. If DR is not treated at the right time, it can cause to irreversible loss of vision [8].

Exudates are one of the parameters that deduce the presence of DR in a diabetic patient [9]. The lipid fluids that leak from the blood vessels accumulate in the retinal region, and these deposits are known as exudates [10]. There are two types of exudates – Hard Exudates and Soft Exudates [11]. Soft exudates are the accumulation of the ruptured vessel debris. These are usually oval or round in shape and white or pearly white in color. These are found in fewer numbers and usually lie near the optic disc. Hard exudates are small or large deposits of the lipids. These appear waxy or yellowish white in color and are found in large numbers, usually underneath the blood vessels. The ophthalmologists acutely examine these exudates using a specialized camera called the Fundus camera [12].

One of the most researched works conducted all around the globe, is to automate the process of exudate identification, to help the patients in the rural areas, who are deprived of ophthalmologists and good facilities to tackle eye related complications. The retina consists of dark and bright areas. Exudates, blood vessels and optic disk have higher contrast than any other parts of the eye. Thus extracting exudates based on only one parameter might always not result in true positives. Thus, extracting only the exudates is a complex task. This particular review paper discusses about various approaches implemented by several authors to solve our problem statement. Section 2 introduces the concepts of preprocessing and segmentation applied for automated exudate extraction as described in the papers reviewed mentioned in Section 3. Section 4 concludes the paper by presenting the scope for the future work related to automated exudate detection.

II. PREPROCESSING

It is a well known fact that the fundus image obtained from the camera is prone to noise and uneven brightness [17] and hence before the actual extraction steps are performed, preprocessing is a must and should. Preprocessing is a crucial stage that nullifies the noise and other unwanted features of the retinal image such as blood vessels. In most of the research carried out, it was found that exudates have a higher contrast in the green (G) channel of the RGB image and therefore exudates are extracted using the green component. Few of the popular preprocessing methods have been described below.

One major issue faced in image processing, is the problem of extracting spherical objects. The major reason for this is that they cannot be uniformly illuminated. The same concept holds good for the eye as well. The center of the fundus image is more illuminated than the rest of the retinal area and hence extraction becomes a major issue.

Amongst various methods to obtain uniform illumination, one of the most popular methods is median filtering. The average of all the pixels included under a sliding window of size m x n is found out and this replaces the center pixel of the window as dealt in [13, 18, 19].

Another methodology has been elaborated in [20] wherein authors state that by subtracting the results obtained from top-hat and bottom-hat transforms of the green channel, the image becomes uniformly illuminated.

Other methods include the one explained in [21], wherein the fundus image is converted to the HSV color model. The V channel is extracted and median filtering is applied. It is then later enhanced in terms of contrast using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method [22] where Adaptive Histogram Equalization (AHE) is a technique of dividing the entire image into small sections and performing histogram equalization for each segment. This is established using CDF to map the pixels in the region to enhance the contrast of the image [16]. AHE is highly prone to enhancing noise as well present in these segments. Contrast Limited AHE (CLAHE) is the improvised version of AHE, which does not amplify the noise. The transformed V component is combined with the H and S channels and converted back to the RGB color model, thus resulting in removal of noise.

In a few cases such as [23], [24], [25], both median filtering and CLAHE method are utilized for noise removal on the grayscale component of the image which showed better performance than using one method alone.

Papers such as [18], [26], [27], [28] perform contrast enhancement by converting RGB model to YIQ color space, replacing Y with weighted sum of Y, I and Q components and converting back to the RGB color model. Once the new model is obtained CLAHE is performed for better enhancement. [29], [18], [30], [31] also utilize CLAHE for image enhancement. This method is also comparable to the green channel extraction as discussed above.

As per [32], the local contrast enhancement (LCE) process is applied on the median filtered output to enhance the contrast of the image to the best level. In [33], the RGB model is converted to HSV color space and the LCE process is induced for enhancement. According to [34], in order to enhance the image, histogram specification for even frequency distribution is applied followed by the LCE approach.

[18], [26] also propose a method to brighten the exudates even more by performing white top-hat (WTH) transformation. Top-hat transformation is a procedure applied when small details have to be extracted from the image. This transformation comes in two variants – white top-hat transformation and black top-hat transformation. The former is the difference between the original image and the opened image. The latter is the original image subtracted from closed image [14]. Black top-hat transformation is also known as Bottom-hat transformation [15]. WTH transformation showed better result than a simple averaging filter.

[35] proposes to apply averaging filter to highlight only the bright areas of the retina. Later, the green channel is extracted and contrast stretching transformation is performed to brighten the high contrast areas even more. Contrast stretching transformation is also used in [36] on the grayscale component of fundus image.

Morphological fuzzy based closing operation with a diamond shaped structuring element is performed on the contrast enhanced image, as explained in [36]. The resultant image is then added with the original image to highlight exudates. This is used in enhancement of exudates.

Another major issue faced apart from non-uniform illumination, is the effect of blood vessels on the image utilized for exudates extraction. Several approaches have been discussed on this topic as well.

In [37], the authors describe a methodology that utilizes median filters, to extract blood vessels. Several other approaches such as [20], [38] propose to remove blood vessels by extracting the green component and applying a high pass filter for contrast enhancement. Morphological closing with a large structuring element is performed for the complete vessel removal. The morphological closing concept has also been used in [18], [24], [39] as well.

Once the preprocessing steps are complete, the next major step would be to extract the exudates and the procedures for the same have been elaborated in the next section.

III. SEGMENTATION OF EXUDATES

The preprocessed image obtained using any of the methods explained in the above section, is now utilized for the segmentation of the exudates. The main challenge faced here is that the intensity-contrast characteristics of the exudates and the optic disk appear the same. Many authors have proposed algorithms where the optic disk is eliminated first and then exudates are extracted; while there is another set of authors who propose segmentation algorithms in association with feature extraction that are fed to classifiers to correctly identify the exudates and discard the optic disk and other bright areas of the retina. Both the categories have been explained below.

[37] uses the histogram based thresholding approach, wherein the local minima of the histogram is considered. All small fluctuations are nullified, and the last minimum is considered as the threshold. This threshold is applied to extract exudates along with the optic disk. It is a well known fact that the blood vessels in the eye converge at the optic disk. Thus, the authors find out the converging point of the blood vessels and the bright area that houses this intersection point is considered as the optic disk, while the rest are declared as exudates. An accuracy of 89%, sensitivity of 92.87% and predictive value of 96.03% is achieved.

Edge based segmentation methods can also be employed for exudates extraction. This can be seen in [23], where the authors use the Canny edge detector to identify the variations in grayscale intensity values of the retinal image that results in edges. These boundaries are optimized using a gradient image to eliminate the optic disk. The blood vessels are removed by morphologically closing the image. In order to refine the results, closing is performed once more to get only the exudates.

In [28], edge detection is used for segmentation. The gradient of the original image is obtained. Once the edges are acquired, they are sharpened with the ramp width reduction technique, which utilizes gradient values previously attained.

Another approach which utilizes edge based segmentation has been described in [40], wherein the green channel of the fundus image is morphologically dilated. Due to the bright features of exudates, the edges appear prominent. Dilation is then performed twice with different structuring element sizes and the difference between the dilated images results in the edges of the exudates. These edges are then filled via morphological reconstruction. Thresholding on the reconstructed image leads to a binary image that contains only exudates. The same concept is used in [41].

A simple thresholding method can also be used to extract the exudates by choosing an appropriate threshold level, as showcased in [20]. In [42], the preprocessed image is complemented and with a threshold of 0.97, segmentation is performed. The binary image is then morphologically closed and opened for removal of blood vessels and optic disk, with a circular structuring element. Sensitivity of 96.89% and specificity 97.15% is achieved, but accuracy is not reported.

Another approach for exudate segmentation, as demonstrated in [25] is to carry out marker based morphological reconstruction, which is performed after blood vessels and the optic disk are removed using morphological dilation. Closing operation is performed with a line structuring element of 15 and 9 corresponding to width of widest and narrowest vessels. The exudate extraction is reported to be good but there is no indicators measured.

[35] discusses about the Watershed approach to extract exudates. After preprocessing, the contrast adjusted image is used to obtain gradient magnitude and internal markers are identified using the extended minima transformation. Also, an external marker is obtained to divide the image effectively into regions. Using these markers, the gradient image is modified using the minima imposition approach. The modified gradient image helps to get regional minima only in the marker areas. Watershed algorithm is then applied on this modified gradient for exudates extraction. Predictive value is used as the performance indicator which is 91.9%. The algorithm complexity is not discussed.

[38] proposes to use K-means clustering method for segmentation. In most cases of data analysis, mean and covariance would not be sufficient to extract information from a huge set of data. Instead different data clustering algorithms can be implemented. One of the popular clustering algorithms is k-means clustering [45]. The data is classified by dividing it to 'k' number of non-overlapping clusters. The grouping is done in such a way that there is a high degree of similarity within each group and low degree of similarity with different groups. Each cluster is identified with a centroid. The k-means algorithm is an iterative approach of refining similar kinds of data to be grouped together. During each trial of iteration, the centers of the clusters might change its position to obtain accuracy; but once all the groups are distinguished from each other and there is no chance of similarity, then the iterative process stops and the centers don't move further. The distance between the centers of the clusters obtained and the nearby pixels is calculated and the pixels with minimum distance are considered. The average of these pixel values is calculated till convergence is obtained. For machine learning, a trained set of images is acquired using the Principle Component Analysis (PCA). PCA is a data analyzing technique, which is often used for data reduction without any loss of information and data interpretation [46]. This is a multivariate technique where in the statistics or simultaneous observation and analysis of the outcome variables is conducted. The outcomes are studied and described by several quantitative dependent variables which are inter-correlated. The information from the data set is extracted and is stored as a set of orthogonal values known as 'Principal Components'. The components are known as orthogonal values since they are the Eigen Vectors of the symmetric Covariance matrix. The number of these principal components are often lesser than or equal to the original number of variables. The characteristics of these components are plotted and a study on their similarities is conducted. The largest possible variance decides the first component. The succeeding components have the highest variance possible under the limitation that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. The PCA algorithm is sensitive to the relative scaling of the original variables. The Gaussian description method is used along with PCA and these images are used for exudate identification. Though the detection accuracy is good the performance of the algorithm has to be improved for early detection of DR.

The preprocessed image obtained in [21] is converted to L*a*b* color space and using the Fuzzy C-means (FCM) clustering algorithm, clusters are identified in the a* and b*channels, which indicate exudates and optic disk. A specialized FCM clustering approach called the Spatially Weighted FCM clustering can also be applied for segmentation as in [32], [33]. The algorithm in [32] has to be improved to classify the segmented image into exudates and non-exudate patches.

[18] proposes different methods through which exudates can be extracted. The first method explains that for a sliding window, the standard deviation (SD) is estimated, and this SD value is used as a threshold only in the window area. The binary image obtained is morphologically reconstructed to perform hole filling. The original and reconstructed images are subtracted and a simple threshold is applied on the difference image obtained to extract bright regions. A similar method has been proposed in [39], [31]. In the second method, global histogram analysis is performed and a threshold t1 is obtained. Similarly, using local histogram analysis a threshold t2 is acquired. This results in two binary images. These images are logically ANDed to get a segmented image that consists of only bright areas. Another approach explained in this paper, is that different features can be considered, which can be used to obtain clusters from the FCM clustering method [30]. This image is considered as a marker and the original image is considered to be a mask. Morphological reconstruction is performed and is subtracted with the original image. Thresholding is applied on the difference image to get only the bright regions. The resultant images of all steps are fed to an Adaboost classifier to extract only the exudates. Similar methods have been proposed in [26]. The accuracy is reported to be better than previous results, but there is a mixture of different pre-processing and segmentation methods and the whole process is not simple.

[43] Proposes that once the image is preprocessed, histogram can be used to obtain the threshold for segmentation. Later different features of the bright areas are fed to a Multilayer Perceptron (MLP) classifier to yield only exudates.

The authors of [34] use the Gaussian-smoothed histogram analysis and FCM clustering methods to extract exudates. In case of the Gaussian-smoothed histogram analysis, the histogram for all the coloured layers is estimated. Later, using a Gaussian function, the histogram is smoothed to remove all minor peaks and valleys. The valleys now obtained can be used for thresholding. The predictive value reported is 89.3% and the algorithm has to be improved for early stages of DR.

Segmentation can also be performed by dividing the image into different regions and processing it further. According to the approach utilized in [29], the preprocessed image is resized to 800x800 pixels and is divided into sub-regions of 80x80 pixels. All the abnormal regions are identified and Gray-level Co-occurrence Matrix (GLCM) is introduced to obtain 13 features of the abnormalities, which are then fed to a Support Vector Machine (SVM) Classifier that is capable of identifying only the exudates. Similar concepts are used in [18], [21], [24], [44]. An accuracy of 71.94% for SVM method and 74.53% for multilayer perception method is reported which needs an improvement.

[47] deals with minimum distance classifier which calculated the distance between unknown and each of the prototype pattern vector. Based on the smaller distance, the output is decided. Size, shape, color, brightness are some of the characteristics used to delineate the objects in an image.

[48], [49] uses the combinations of the method discussed, that is thresholding and morphological operations to extract the exudates

The severity of diabetic retinopathy is dealt in [49]. The segmentation is based on JSEG (abbreviated for J value Segmentation) algorithm , which is an unsupervised segmentation process for image and video. This includes color quantization and spatial segmentation. It is reported that the severity is high if the distance between the detected exudate and macula is smaller and vice versa.

In this way, there exists several methodologies to perform both preprocessing and extraction of the exudates from the Fundus image of the eye. The next section describes the significant findings, conclusion and possible future scope of the research carried out in this paper.

IV. CONCLUSION & FUTURE SCOPE

In this paper, a collation of various methodologies to perform both preprocessing and extraction of exudates have been presented. As explained in Section III, most of the methods utilize the green channel component along with algorithms such as the median filtering approach and Contrast Enhancement for preprocessing. With respect to exudates extraction, it can be concluded based on comparison of the results obtained from all the sources mentioned in Section IV, that utilizing the histogram based approach along with morphological operations give an accuracy of more than 90%. This ensures a total reduction in the number of false positives obtained.

Though all the techniques mentioned in this paper sound promising in terms of accuracy, a major cause of concern would be the necessity of a high speed algorithm which must complement this accuracy obtained. This is mainly due to the reason that along with an accurate result, there is also a need of a faster diagnosis in turn leading to quicker healing times and reduced delay in prognosis, thus saving eyesight as quick as possible. Hence, it becomes the need of the hour for future research work to concentrate on the same.

Also, most of the research carried out, perform deployment of algorithms on a computer, either a desktop or a laptop and none of the research actually concentrates on implementation on a handheld device. By employing an Application Specific Integrated Circuit (ASIC) approach, not only does it promise a low power solution but also an economically viable one. Research carried out in this direction would prove to be extremely advantageous especially for the eye disease treatment in developing nations where access to healthcare is a very costly affair.

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