A Computer Aided System for Grading of Maculopathy

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Abstract—In medical imaging, digital images are analyzed to develop computer aided diagnostic (CAD) systems using state of the art image processing and pattern recognition techniques. Diabetic maculopathy is one of the retinal abnormalities in which diabetic patient suffers from severe vision loss due to affected macula. In this paper, we propose an automated system for the grading of diabetic maculopathy to assist the ophthalmologists in early detection of the disease. We present a three stage system consisting of macula detection, exudate extraction and grading of maculopathy. First stage uses optic disc and blood vessels to extract macula from retinal image. Exudate extraction stage extracts all possible exudates from retina using filter bank and support vector machines. Finally, the system grades the input image in different stages of maculopathy by using the macular coordinates and exudate feature set. The evaluation of proposed system is performed by using publicly available standard retinal image databases.

I. INTRODUCTION

The research in medical imaging is of great significance in this modern era. The study in this field will greatly benefit the health care systems and society. One of the common diseases all over the world is diabetes in which the lack of insulin causes high blood sugar in humans. The long term diabetes also affects the human retina resulting in a condition known as diabetic retinopathy (DR). This condition damages the retinal blood vessels causing them to leak which ultimately leads to blindness [1].

There are several stages of DR and maculopathy is one of these in which macula is surrounded by the exudates and patient’s central vision is affected. Exudates are yellowish deposits of protein present in the retina which are caused by the leakage of blood from blood vessels. Macula is accountable for the clear, sharp and detailed vision [1]. The center of macula is called fovea which is responsible for very fine details in the image. Diabetic maculopathy occurs if exudates appear on or near the macula affecting central vision. The human visual loss can be prevented by early screening and diagnosis of diabetic maculopathy. The two types of macular edema are non clinically significant macular edema (Non-CSME) and clinically significant macular edema (CSME). Non-CSME is a mild form of maculopathy in which there are no symptoms of the disease because the locations of exudates are at a distance from fovea and the central vision is not affected. CSME is the severe form of maculopathy in which the exudates leak out and get deposited very close to or on fovea affecting central vision of the eye [2].

A number of complete systems for maculopathy detection have been proposed by different authors. Shahawy et. al [4] proposed a method for segmentation of diabetic macular edema in fluorescein angiograms. Their proposed method is based on modeling the macular image in early time frame using 2D Gaussian surfaces which is then subtracted from the late time frame image to enhance the macular edema regions. The resulting difference image is segmented using GMM classification algorithm. The proposed method gives good results on local dataset. In [9], the diabetic macular edema is classified in which marker controlled watershed transformation is used for exudates feature extraction. The exudates from the fundus image are extracted and their location along with marked macular regions is utilized for the classification of maculopathy into different stages. The method was tested on MESSIDOR database and the sensitivity is found to be 80.9% and specificity of 90.2%. Deepak et. al [10] proposed a method for automatic assessment of macular edema using supervised learning approach to capture the global characteristics in fundus images. Disease severity is assessed using a rotational asymmetry metric (motion pattern) by examining the symmetry of macular region. The method is tested on publicly available databases like diaretdb0, diaretdb1, MESSIDOR and DMED. The accuracy for the maculopathy detection is found to be 81%. [11] presented a method for classification of exudative maculopathy using FCM clustering and artificial neural networks. The authors have reported sensitivity of 92% and specificity of 82% on some local dataset. In [3], the automated system for grading of diabetic maculopathy is proposed. The macula is localized and hard exudates are detected using clustering and mathematical morphological techniques. Based on the location of exudates, the severity level of diabetic maculopathy is defined in a marked region of macula in abnormal fundus image. The method is tested on local dataset and the sensitivity and specificity were found to be 95.6% and 96.15% respectively.

This article consists of four sections. The proposed system and its complete explanation are given in section 2. The experimental and comparative results of proposed system using different evaluation parameters and databases are elaborated in
section 3 followed by discussion and conclusion in last section.

II. PROPOSED METHODOLOGY

The percentage of diabetes patients is high in almost every region of the world especially in industrialized countries which makes a high chance of DR sufferers. Automated screening of human retina and detection of early signs can save patients vision so it is important to develop CAD systems for retinal diseases. In this article, we present a system for grading of maculopathy to save sudden vision loss. The proposed system consists of macula and exudate detection and finally grading of maculopathy. The algorithms improve the quality of automated system by eliminating blood vessels and optic disc (OD) pixels to ensure the reduction in false positives and a detailed feature set for accurate detection of exudates.

A. Macula Detection

First stage of proposed system is detection of macula and its coordinates. Macula detection is an important module for developing the computerized system for the grading of diabetic maculopathy. It is the macular area of the eye that is affected in diabetic maculopathy upsetting the central vision of the eye and in severe cases leading to blindness. The technique which we have used for macula detection is described in [19]. In this technique macula is first localized with the help of localized OD and enhanced blood vessels [20]. Finally macula is detected by taking the distance from the center of optic disk along with enhanced blood vessels image to locate the darkest pixel in this region, and making clusters of these pixels. The largest cluster formed is macula.

B. Exudates Extraction using Support Vector Machine

The proposed system extracts exudates as its second stage using filter bank and support vector machine. This stage is further divided into three phases i.e. candidate exudate extraction, feature extraction and classification using support vector machine.

1) Candidate Exudate Extraction: Candidate exudate extraction phase tries to find all possible regions which may be consider as exudates. It creates a binary map for candidate regions which are further classified as exudate or non-exudate regions using support vector machine. Followings steps are used for candidate exudate detection:

- Take preprocessed image as an input and apply morphological closing to remove the effect of blood vessels and dark lesions
- Apply adaptive contrast enhancement technique to improve the contrast of exudates on retinal surface
- Create filter bank given in equation 1 based on Gabor kernel and convolve it with contrast enhanced image to further enhance the bright lesions [17]

\[
G_{FB} = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(\frac{\Delta x}{\sigma})^2+(\frac{\Delta y}{\sigma})^2}(d_1(\cos \Omega + i\sin \Omega)) \tag{1}
\]

where \( \sigma, \Omega \) and \( r \) are the standard deviations of Gaussian, spatial frequency and aspect ratio respectively \( \theta \) is the orientation of filter and \( d_1 = x\cos \theta + y\sin \theta \) and \( d_2 = -x\sin \theta + y\cos \theta \) [17].

- Create binary map containing candidate exudate regions by applying adaptive threshold value \( T \) which is calculated using OTSU algorithm [15]
- Detect OD using averaging and Hough transform given in [18] and remove all OD pixels from binary map.

Exudates appear as bright regions and have close similarity with OD and it is necessary to remove all OD pixels before going further to eliminate all spurious regions.

2) Feature Extraction: Candidate exudate extraction phase extracts all possible regions for exudates and creates a binary map containing potential exudate regions. In second phase of exudate extraction, we create a feature vector for all regions present in binary map of candidate exudates. The description of features, we used for classification of exudate and no exudate regions are as following:

- **Area** \((f_1)\), is the count of number of pixels in candidate exudate region and defined as \( A = \sum v_i \) 1 sum of all pixels in candidate region \( v_i \).
- **Compactness** \((f_2)\) is measure of shape defined as \( C = p^2/(4\pi A) \) where \( p \) and \( A \) are the perimeter length and area of candidate region respectively.
- **Mean Intensity** \((f_3)\) is the mean intensity value of contrast enhanced green channel for all pixels within the candidate region.
- **Mean Hue** \((f_4)\), **mean Saturation** \((f_5)\) and **mean Value** \((f_6)\) for each candidate region are calculated in order to differentiate exudate and non exudate regions on basis of their color properties.
- **Mean gradient magnitude** \((f_7)\) for edge pixels is computed to differentiate between strong and blur edges.
- **Entropy** \((f_8)\) value of all pixels in square region including candidate region pixels and its neighboring pixels.
- **Energy** \((f_9)\) is calculated by summing the intensity values of all pixels within the candidate region and dividing it by total number of candidate region pixels.

3) Support Vector Machine (SVM): The last phase of exudate extraction is classification and we use support vector machine (SVM) for this purpose. The complete feature vectors containing features for candidate regions are fed to SVM and it grades the candidate region as exudate and non-exudate region. SVM is famous due to its good classification and rapid training phase. The original algorithm of SVM separates different regions from each other with maximum margin by using a separating hyperplane if the classes are linearly separable. For a linearly separable data labeled \( v_i, y_i, v_i \in R^N, \ y_i = \{-1,1\}, i = 1, ..., N \), hyperplane can be represented by \( w \) and \( b \) such that

\[
y_i(w \cdot v_i + b) > 0 \tag{2}
\]

where \( y_i \) is the class of \( i^{th} \) feature vector \( v_i \). Two hyperplanes are generated using \( w \) and \( b \) such that no sample lies between these planes and all samples with \( y = 1 \) should be on one side of planes and samples with \( y = -1 \) should be on other side.
The distance between these two planes is defined as

$$\text{margin} = \frac{2}{\|w\|}$$

(3)

It is desirable to maximize the distance or margin between planes by minimizing $w$. One consideration is that there should not be any sample between these plane. So, we can rewrite equation 2 such as

$$y_i(w \cdot v_i + b) \geq 1$$

(4)

A problem with equation 4 is the dimensions of $v$ which makes the optimization of $w$ very difficult and a solution can be found using Lagrange multipliers $\alpha_i$ such that $w = \sum_{i=1}^{N} \alpha_i y_i v_i$ and $\sum_{i=1}^{N} \alpha_i y_i = 0$. Now the optimization of $w$ depends directly on optimization of $\alpha$ and only those samples contribute in determining the hyperplane which are corresponding to nonzero $\alpha_i$. These samples are known as support vectors and the decision rule can be defined as

$$y(v) = \text{sign}\left(\sum_{i=1}^{N} (\alpha_i y_i K(v, v_i) + b)\right)$$

(5)

where $K(v, v_i)$ is any kernel function used to make nonlinear feature map by mapping the input feature space to higher dimensions space. We use SVM with a nonlinear kernel function based on radial basis function (RBF) defined as

$$K(v, v_i) = \exp(-\gamma \|v - v_i\|^2)$$

(6)

To implement SVM along with RBF, we have applied least squares SVM using LS-SVM toolbox [21]. In LS-SVM, the multiclass solution is found by solving a system of linear equations instead of original quadratic programming as given in equation 4.

Figure 1 shows the outputs for macula and exudate detection.

![Fig. 1. a) Macula detection; b) Filter bank response; c) Exudate detection using SVM](image)

**C. Grading of Maculopathy**

The last stage of proposed system is the grading of input image for possible maculopathy. Once the classifier has detected all exudates and macula, the system grades the input image as healthy, Non CSME and CSME. The grading is based on the location and distance between macula and exudates if present in retinal image. If the image contains no exudates it will be consider as healthy whereas for non CSME and CSME the retinal image should contain exudates. If the exudates are with one OD diameter distance from macula center it is graded as CSME otherwise system will grade the image as non CSME.

**III. EXPERIMENTAL RESULTS**

The evaluation of automated medical systems is very important and should be done carefully. We have used two standard retinal image databases i.e. MESSIDOR [12] and STARE [13]. MESSIDOR database has been established to facilitate computer aided DR lesions detection especially to grade ME. It contains total 1200 images which are divided into three sets of 400 images and each set is further divided into 4 parts to facilitate thorough testing. STARE database contains total 81 retinal images which are acquired using TopCon TRV-50 retinal camera with 35° Field Of View (FOV) out of which 30 are from healthy retinal and remaining 50 contain different lesions related to DR. Figure 2 shows different retinal images classified as healthy, Non-CSME and CSME by the classifier.

![Fig. 2. Maculopathy detection. a) Healthy retinal images; b) Non-CSME or grade 1 images; c) CSME or grade 2 images](image)

For detailed statistical evaluation, the performance of proposed system is measured using sensitivity, specificity and accuracy as figures of merit. Sensitivity is true positive rate and specificity is true negative rate. Table I shows the comparison of proposed system with existing methods in the literature for macula detection. The table shows that our proposed system yields competitive results as compared to other results in the literature.

**TABLE I**

<table>
<thead>
<tr>
<th>Method</th>
<th>Database</th>
<th>Images</th>
<th>Acc (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sagar et al. [5]</td>
<td>DRIVE, STARE</td>
<td>121</td>
<td>96</td>
</tr>
<tr>
<td>Sinhanthoythin [6]</td>
<td>Local</td>
<td>112</td>
<td>90</td>
</tr>
<tr>
<td>Tan et al. [7]</td>
<td>Local</td>
<td>162</td>
<td>98.8</td>
</tr>
<tr>
<td>Lu et al. [8]</td>
<td>DRIVE, STARE</td>
<td>121</td>
<td>97.7</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>MESSIDOR</td>
<td>1200</td>
<td>97.2</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>STARE</td>
<td>81</td>
<td>97.53</td>
</tr>
</tbody>
</table>

The variation in the accuracy of the system is highlighted with the help of Receiver Operating Characteristics (ROC)
curve which shows relation between true positive rate (sensitivity) and false positive rate (1-specificity). Figure 3 shows ROC curves for grading of maculopathy using MESSIDOR and STARE databases. The system achieves 0.967 and 0.973 as area under the ROC curves for MESSIDOR and STARE databases respectively.

![ROC curve](image)

Fig. 3. ROC curves for proposed system using STARE and MESSIDOR databases

The comparison of complete system for grading of maculopathy is given in table II. The validity of our system is clearly highlighted here even with a use of large number of images.

<table>
<thead>
<tr>
<th>Author</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Siddalingaswamy et. al. [3]</td>
<td>95.6</td>
<td>96.15</td>
<td>-</td>
</tr>
<tr>
<td>Lim et. al. [9]</td>
<td>80.9</td>
<td>90.2</td>
<td>-</td>
</tr>
<tr>
<td>Deepak et. al. [10]</td>
<td>95</td>
<td>90</td>
<td>-</td>
</tr>
<tr>
<td>Osareh et. al [11]</td>
<td>92</td>
<td>82</td>
<td>-</td>
</tr>
<tr>
<td>Aquino et. al. [16]</td>
<td>-</td>
<td>-</td>
<td>96.51</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>96.7</td>
<td>98.29</td>
<td>97.62</td>
</tr>
</tbody>
</table>

**TABLE II**

**COMPARISON OF OUR PROPOSED METHOD WITH EXISTING TECHNIQUES FOR GRADING OF MACULOPATHY**

**IV. CONCLUSION**

Diabetic maculopathy is an advance level of retinal abnormalities which may be present in diabetes sufferers. This may cause total blindness if not detected and treated in time. In this paper, we presented a computerized medical system for automated screening of diabetic maculopathy. The proposed system performed retinal image analysis for grading of maculopathy using a three stage technique. First two stages extracted macula and exudate respectively then using coordinates of macula and the distance of exudates from macula, the system graded the input image into three categories i.e healthy, Non CSME and CSME. The evaluation of proposed system is done using two standard retinal and the results demonstrated that the proposed system can be used in automated medical system for grading of diabetic maculopathy.

**REFERENCES**