Abstract - The detection of anatomical structures of fundus image like the OD, fovea and the retinal vessels is very significant in the automated detection of DR. This review outlines the principles, methods and algorithms used in the automated detection of diabetic eye diseases. The recent methods used to detect fundus image features like the optic disc (OD), fovea and retinal blood vessels, pathologies like hemorrhages, Micro aneurysms (MA), cotton wool spots and retinal exudates are discussed. We discuss the automated detection of diabetic eye diseases using image processing methods. We present the quantitative evaluation of different methods. We also discuss methodologies used by the researchers in analyzing their results.

Keywords—Fundus image, Diabetic Retinopathy (DR), macula, optic disk, exudates, morphological operators

I. INTRODUCTION

Diabetes mellitus is one of the major causes of irreversible preventable blindness worldwide. Long term diabetes can cause the blood vessels to leak blood onto the retina leading to loss of vision and even blindness. Diabetic related eye diseases like diabetic retinopathy (DR) and diabetic maculopathy (DM) has been recognized as a leading cause of visual loss worldwide. Early diagnosis is very important in preventing visual loss in diabetic patients. Rapid increase in the number of instances of diabetes pushes the limits of the current DR screening capabilities for which the digital imaging of the eye fundus (retinal imaging), and automatic or semi-automatic image analysis algorithms provide a potential solution. The process of grading the eye fundus images is time consuming and repetitive, and requires attention of an ophthalmologist. Many of these images may not have any pathologies of the disease. The work of ophthalmologist greatly increases as the progress of the disease needs to be reviewed frequently. The ophthalmologist could give more time for patients which require their attention rather seeing each and every fundus image. This can be done by automating the grading process by which more patients can be screened and if require can be sent for further examination. The speedy growth of information processing system and the emergence of inexpensive ophthalmic imaging devises have led to the development of automated techniques for detection of diabetic eye diseases. Several automated techniques are designed and being used for practical applications. It is very difficult to achieve the concept of generalization among these automated techniques. In order to highlight their suitability for the automated identification of diabetic related eye diseases, it is necessary to analyze various available techniques. This paper provides analysis of various automated techniques along with their strength and weakness. In this review we discuss various algorithms on automated detection of retinal features based on digital image analysis. We also discuss the various methods of evaluation used for automated identification of DR and DM.

The fundus image in figure 1 shows various anatomical parts of retina such as OD, fovea, blood vessels and abnormalities like HMA and exudates. After these features were detected automatic detection of the presence of diabetic retinopathy and maculopathy can be done. The process of feature detection and classification of DR is as shown in figure 2.
II. IMAGE PREPROCESSING

The eye images are normally photographed in non-uniform lighting environments. Before we apply any image processing techniques for feature analysis, these images need to be pre-processed. The image pre-processing technique makes all the eye images to have same color appearance. The contrast of the image can also be equalized using histogram equalization. Histogram equalization is performed on each image to get uniform color appearance over the entire image dataset.

Image contrast of the digital fundus image decreases as the pixel distance is increased from the image centre. This can be minimized using image preprocessing and the mean intensity can also be normalized. Initially the RGB color band is transformed into IHS (intensity-hue-saturation) representation. With this transformation we can process the intensity without modifying the perceived relative color pixel values. The local contrast enhancement function increases the contrast of poorly contrasted image and decreases the contrast of highly contrasted image. This leads to the dark area to become brighter showing the details very clearly but increases the noise. The noise can be suppressed by applying a spatial filter (smoothing or median) before the enhancement process.

III. DETECTION OF RETINAL LANDMARKS

The detection of anatomical structures of fundus image like the OD, fovea and the retinal vessels is very significant in the automated detection of DR. Novel methods to localize OD, fovea, and retinal vessels can be found in the literature. We will review few papers which show promising results.

A. Detection of Optic disk

Identification of the OD is very significant in locating other features of retinal fundus image such as blood vessels and fovea, in measuring cup to disk ratio for the detection of Glaucoma and for observing changes due to DR and DM within the OD region. In the fundus image OD appears as an orange or pink region measures about 1.5mm in diameter. The size, location and appearance of the OD vary in fundus images. Over the last 25 years many researchers have detected the OD in fundus using different techniques. Lee et al., 1989 [1] detected the OD using their high pixel intensity with a high grey scale value. The method fails when there are lesions with similar high grey scale values [2]. A method based on PCA (Principle component analysis), where the clustered brightest pixels are used as candidate optic disc regions [3]. PCA was applied and centre of the OD was marked by finding the smallest distance between the fundus image and its projection. By applying the intensity variance between the OD and the adjacent retinal vessels Sinthanayothin et al [4] detected the optic disk. This technique fails in the presence of white lesions and choroidal vessels [5]. Hough Transform has been used for the identification of the OD [6] by a number of researchers. The technique fails to give the best result as the Hough space is sensitive to the image resolution. In recent years to detect the OD geometric parametric model [7], Fuzzy convergence [8] and contour model based approaches [9] were used.

B. Detection of Fovea

The foveal centre can be detected from the optic disk centre at a distance of 2.5times the OD diameter. In the entire fundus image fovea is the darkest and has the same intensity as that of blood vessels. It is usually detected by exploiting its avascularity with different grey levels at its boundary [10]. Li et al detected the regions with fovea, using model-based techniques [3]. Sinthanayothin et al [4] identified the fovea as the position of maximum correlation between a model template and intensity image.

C. Detection of retinal vessels

The prominence of retinal vessels upon the retina is very significant feature in the automated detection of DR. The vessel detection finds the application in measuring the disease severity and the treatment effect can also be assessed [11]. To detect the retinal vessels we find a lot of image processing techniques used in the literature.
D. Detection of Micro aneurysms and Hemorrhages

In the literature we find many publications for the automated detection of MA. It plays as important role in the computer assisted detection of DR. In the green channel of RGB, MA appears as tiny isolated circular dark patterns, where as in FA they have the same shape characteristics but appear as better contrasted with bright patterns. Lay et al [17] used the morphological opening with linear structuring element and using Top hat transform extracted the details which may corresponds to MA. A bilinear top hat transformation is used to differentiate the circular and linear segments of MA [18].This leads to false vessels detection as many segments with vessels are not linear and remains after the transformation. Using a Mahalanobis classifier micro aneurysms and Hemorrhages were identified respectively with a sensitivity of 69% and 83%[19].Image processing techniques along with pattern recognition were used to detect MA’s and hemorrhages using fundus images [20]. A recursive region-growing technique with Moat operator was employed by Sinthanayothin et al. (2002) [16].

E. Retinal exudates and cotton wool spots detection

Exudates are directly related to retinal Edema and visual loss, and they are the single most important retinal lesion detectable in retinal images. The exudates appear as bright patterns and their contrast is very bright compared to the background. Automated detection of exudates becomes very challenging as the other retinal features such as blood vessels and OD also have the similar brightness patterns and grey level variations. Exudates were identified using the recursive region growing algorithm [16] using fundus images. Walter et al have found the exudates in the fundus images using their high grey level variations and morphological reconstruction techniques [21].The algorithm does not differentiate the exudates from cotton wool spots. Neural networks based approach was used to locate exudates in [22]. A Fuzzy C-means clustering technique [23] and a Computational intelligence technique [24] were used for the identification of exudates.

F. Automated detection of DR using digital fundus image analysis

Diabetic related eye diseases such as DR and DM are the main reason for visual loss in the world. Visual loss can be prevented or delayed, if the symptoms are diagnosed early and the patients are treated properly. Digital fundus photography is used in screening programs across the world in order to address the impact of Diabetic Retinopathy. Many of the current detection schemes show unacceptable specificity which is a hindrance for the automated diabetic detection program. Usher et al [25] has given the reasons for the difficulty in differentiating drusen from exudates because of the potential problems with different pigmentation form different ethnic races. Since the sensitivity is significant measure than specificity many researchers have proposed highly sensitive schemes for the detection of DR. Wong et al. [26] have classified DR into different stages based on the severity of the disease stages using mathematical morphology and a feed forward neural network. Kahai et al [27] used a decision support system for the early detection of DR.A normal retina was differentiated from the diseased retina affected by DR by Sinthanayothin et al. [16] using simple image-processing algorithms. Acharya et al [28] classified DR as normal state, mild, moderate, severe and proliferative DR states by extracting features using higher order spectra(HOS).These features were fed to SVM(Support vector machine ) for classification.

IV. DISCUSSION

In this review the computer-aided algorithms developed to locate the major retinal landmarks like Optic disk, fovea and blood vessels and automated detection of DR were studied. It is found that image preprocessing techniques like color normalization and local contrast enhancement were applied to fundus images to increase the contrast of the image. OD was found using high pixel intensity with a high grey scale value, PCA, Hough transform and Fuzzy convergence methods to name a few. Fovea was detected with different grey levels at the border, using model-based methods, using the position of maximum correlation between a model template and intensity image by various researchers.
Literature shows the detection of retinal blood vessels is done by 2-D matched filter approach, genetic algorithms, 2-D Gabor filters, mathematical morphology, curvature evaluation techniques and PCA.

In the literature for the detection of HMA authors use morphological operators, bilinear top hat transform, Mahalanobis classifier, pattern recognition and a recursive region-growing technique with Moat operator.

Identification of retinal exudates and cotton wool spots can be performed using recursive region growing Techniques, morphological reconstruction techniques, neural networks, Fuzzy C-means and Computational intelligence techniques were used. In the literature we can find a number of publications on automated detection of DR which gives varying degrees of sensitivity and specificity, the summary of which is given in the Table 1. With the recent developments in the field of automated detection of diabetic eye diseases, one can analyze the retinal fundus images and detect the diabetic retinal pathologies without the help of an Ophthalmologist. The techniques reviewed in this paper can be very significant in the automated identification DR and DM in the early stages. With these algorithms the accuracy of DR and DM screening in the early stages can be increased, which subsequently can reduce the work load of Ophthalmologist.

V. EVALUATION METHODOLOGY

The diagnostic test is an examination used in classification of patients into a particular class or clinical state. There are four possible results for the test if the outcome of the examination is binary: true positive, true negative, false positive and false negative. For abnormal test subject, the result is true positive if the diagnostic test outcome is abnormal and false negative if the diagnostic test outcome is normal. For normal test subject, the result is true negative if the diagnostic test outcome is normal and false positive if the diagnostic test outcome is abnormal. For a given set of subjects, the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) can be used to determine the accuracy of the diagnostic test in form of sensitivity (SN) and specificity (SP).

Performance of the test classifier can be measured in the form of sensitivity, specificity and positive predictive accuracy. True Positive (TP) is number of positives outcomes of the test, when compared with the reference of gold standard. This gives number of abnormal cases is correctly classified in the classifier. If the normal sample is classified as abnormal then it is called as False Positive (FP). If the normal is classified correctly then it is it is True Negative (TN). If the abnormal sample is classified as normal then is called as False Negative (FN).

The sensitivity of a test is the probability that it will produce a true positive result when used on diseased population. A sensitivity of 100% means that the test recognizes all sick people as such. Sensitivity can be computed as follows

\[
\text{Sensitivity} = \frac{TP}{TP+FN}
\]

Specificity is a statistical measure of how well a classification test correctly identifies the negative (normal) cases. If the specificity is 100%, then the test can correctly classify all normal patients. Specificity can be computed as follows

\[
\text{Specificity} = \frac{TN}{TN+FP}
\]

The positive predictive accuracy of a test is the probability that the patient has the disease when restricted to those patients who test positive. This term is sometimes abbreviated as PPA. We can compute the positive predictive accuracy value as

\[
\text{PPA} = \frac{TP}{TP+FP}
\]

The ROC (receiver operating characteristic) curve, also known as ROC analysis, is a widely used tool in medical community for visualizing and comparing methods based on their performance[ ]. It is a graphical representation that describes the trade-off between the sensitivity and specificity (e.g., correctly classified normal images vs. correctly classified abnormal images). The method was initially developed to evaluate the classification accuracy in differentiating signal from noise in signal detection. In recent years the methodology has been adopted to various research areas such as in computer vision. The ROC analysis is also an acknowledged methodology in medical research in accordance with medical decision making.

<table>
<thead>
<tr>
<th>No.</th>
<th>Reference</th>
<th>Method</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
</tr>
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<tr>
<td>1.</td>
<td>Olson et al. [29]</td>
<td>HMA or exudates within 1DD of the fovea</td>
<td>83</td>
<td>71</td>
</tr>
<tr>
<td>2.</td>
<td>Singhanayot hin et al.[16]</td>
<td>Moat operator</td>
<td>80.21</td>
<td>70.66</td>
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<td>3.</td>
<td>Singalavanijsa et al.[30]</td>
<td>Retinal vessels, exudates, HMA</td>
<td>74.8</td>
<td>82.7</td>
</tr>
<tr>
<td>4.</td>
<td>Osareh et al.[24]</td>
<td>Exudates</td>
<td>95</td>
<td>88.9</td>
</tr>
<tr>
<td>5.</td>
<td>Usher et al.[25]</td>
<td>HMA</td>
<td>94.8</td>
<td>52.8</td>
</tr>
<tr>
<td>6.</td>
<td>Gardner et al.[22]</td>
<td>Exudates</td>
<td>88.4</td>
<td>83.5</td>
</tr>
<tr>
<td>8.</td>
<td>Osareh et al[35]</td>
<td>Exudates</td>
<td>96</td>
<td>94.6</td>
</tr>
</tbody>
</table>
VI. CONCLUSION

This review paper analyses the merits and demerits of the existing automated techniques for the identification of retinal features and pathologies. In future, we expect to have efficient methods which will help in the early detection of diabetic eye diseases. Ultimately these automated methods will help in screening of diabetic patients without the help of Ophthalmologist.

REFERENCES


