International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-6 Issue-1, October 2016

Detection of Diabetic Retinopathy from Fundus Images through Local Binary Patterns and Artificial Neural Network

Anila V M, Seena Thomas

Abstract— *: Diabetic retinopathy (DR) is one of the most frequent cause of blindness and vision loss in diabetic patients. The diabetic retinopathy is detected earlier, the better the chance that it can be effectively treated and further vision loss prevented. This condition increases the importance of automated detection of the disease. This work focuses on distinguishing between diabetic retinopathy (DR) and normal fundus images by analyzing the texture of the retina background. Local Binary Patterns (LBP) are used as texture descriptors. They are the powerful grey-scale texture descriptors that is commonly used because of its computation simplicity. Local Binary Pattern is based on looking at the local variations around each pixel, and assigning labels to different local patterns and the labels are evaluated and used in the classification stage. Probabilistic Neural Network (PNN) is the classifier that is used for the classification of abnormal and healthy images. This work suggest that LBP is a robust texture descriptor for retinal images and the proposed method analyzing the retina background directly and avoiding difficult lesion segmentation such as exudates, microaneurysms etc. can be useful for diagnostic aid*.

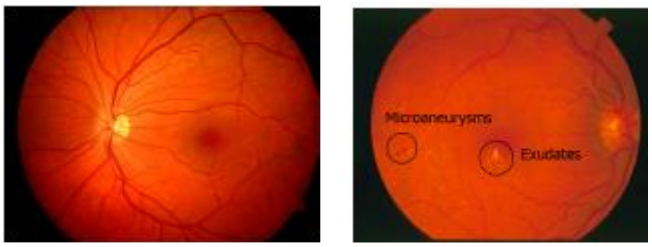
Index Terms— ***Diabetic Retinopathy, Local Binary Patterns, Probabilistic Neural Network, Fundus Images***.

I. INTRODUCTION

Diabetes is a group of metabolic diseases in which a person has high blood sugar either because the body does not produce enough insulin, or the body does not respond to the produced insulin. Diabetic Retinopathy is main complication of diabetes, which damages the small blood vessels in the retina which results the loss of vision.

There are four stages of diabetic retinopathy ranging from mild to severe. They are Mild non-proliferative retinopathy, Moderate non-proliferative retinopathy, Severe non-proliferative retinopathy, Proliferative retinopathy. The symptoms of earlier stages of retinopathy are the Micro aneurysms, which occur due to dilatations of the blood capillaries and they appear as dark red spots on the retina. Hemorrhages occur when the microaneurysms burst. Bright-yellow colored Lesions such as hard exudates occur as a result of fluid leaking into the retinal surface from the capillaries or from microaneurysms. Another bright white colored lesions, called the soft Exudates or cotton wool spots occur occlusions of the nerve fiber layer. In Non-proliferative retinopathy these retinal lesions are appeared and causes the blood vessels become blocked and results short of blood supply. Thus the abnormal and fragile blood vessels are formed on the surface of the retina in the stage of Proliferative retinopathy that might leak blood into retina causing permanent blindness. The early diagnosis allows, through appropriate treatment, to reduce costs generated when they are in advanced states and may become chronic. This fact justifies screening campaigns. screening campaign requires a heavy workload for trained experts in the analysis of anomalous patterns of each disease which, added to the at-risk population increase, makes these campaigns economically infeasible. Therefore, the need for automatic screening systems is highlighted.

Fundus Imaging has an important role in the diabetic retinopathy detection and monitoring. This paper investigates discrimination capabilities in the texture of fundus to differentiate between pathological and healthy images. Local Binary Patterns (LBP) is a texture descriptor for retinal images. It is based on looking at the local variations around each pixel, and assigning labels to different local patterns. Thereafter, the distribution of the labels is evaluated and used in the classification stage. The goal of this paper is to distinguish between DR and normal fundus images at the same time and avoiding any previous segmentation stage of retinal lesions. The texture of the retina background is directly analyzed by means of LBP, and only this information is used to differentiate healthy patients and the diseased.



(a) **(b)**

Fig.1. Fundus images. (a) Healthy, (b) DR (with microaneurysms and exudates)

II. RELATED WORKS

Various eye disease detection image processing, neural network algorithms are proposed in past. Many important eye diseases as well as systemic diseases manifest themselves in the retina.

Manuscript published on 30 October 2016.
***** Correspondence Author (s)
Anila V M, M.Tech Scholar, Department of Computer Science and Engineering, LBS Institute of Technology for Women, Thiruvananthapuram, India.
Seena Thomas, Assistant Professor, Department of Computer Science and Engineering, LBS Institute of Technology for Women, Thiruvananthapuram, India.

While a number of other anatomical structures contribute to the process of vision, this review focuses on retinal imaging and image analysis.

According to Niemeijer et al. [1] there are multiple factors complicating the manual segmentation of the images from the database. The smallest vessels are hard to see, especially if they are not wider than one pixel. JPEG compression artifacts further hamper the segmentation of those vessels. Another effect of the JPEG compression is that the location of the border of larger vessels becomes difficult to establish. A final factor is the time involved in the manual segmentation, it takes on average 2 hours to manually segment one image using a simple painting tool. When segmentation times are this long, fatigue of the human observers can cause a loss in segmentation precision. In comparison with the most accurate automatic method (pixel classification) the second observer still is significantly more accurate, in a paired t-test $P < 0.001$. All other differences in accuracy between the methods are significant as well with a $P < 0.01$. A possible explanation for the fact that the pixel classification outperforms the other methods is the fact that this is the only supervised method (i.e. trained with examples). For a segmentation problem as complicated as the one at hand it is very hard to establish rules which work in all types of situations that can occur in a large set of images.

According to T. Walter,et al. [2] the presence of exudates within the macular region is a main hallmark of diabetic macular edema and allows its detection with a high sensitivity. Hence, detection of exudates is an important diagnostic task, in which computer assistance may play a major role. Exudates are found using their high grey level variation, and their contours are determined by means of morphological reconstruction techniques.

The detection of the optic disc is indispensable for this approach. We detect the optic disc by means of morphological filtering techniques and the watershed transformation. The algorithm has been tested on a small image data base and compared with the performance of a human grader. As a result, we obtain a mean sensitivity of 92.8% and a mean predictive value of 92.4%. Robustness with respect to changes of the parameters of the algorithm has been evaluated.

Frédéric Zana and Jean-Claude Klein [3] presents an algorithm based on mathematical morphology and curvature evaluation for the detection of vessel-like patterns in a noisy environment. Such patterns are very common in medical images. Vessel detection is interesting for the computation of parameters related to blood flow. Its tree-like geometry makes it a usable feature for registration between images that can be of a different nature. In order to define vessel-like patterns, segmentation will be performed with respect to a precise model. We define a vessel as a bright pattern, piece-wise connected, and locally linear. Mathematical Morphology is very well adapted to this description, however other patterns fit such a morphological description. In order to differentiate vessels from analogous background patterns, a cross-curvature evaluation is performed. They are separated out as they have a specific Gaussian-like profile whose curvature varies smoothly along the vessel.

Soares et al. [4] used a Gaussian mixture model Bayesian classifier. Multiscale analysis was performed on the image by using the Gabor wavelet transform. The gray-level of the inverted green channel and the maximum Gabor transform response over angles at four different scales were considered as pixel features. Finally, a support vector machine (SVM) for pixel classification as vessel or nonvessel. They used two orthogonal line detectors along with the gray-level of the target pixel to construct the feature vector.

Keith A. Goatman et al.[5] described a method for automatically deducting new vessels on the optic disc using retinal photography. Aliaa Abdel-Haleim et al. [23] presented a method to automatically detect the position of the OD in digital retinal fundus images. The method starts by normalizing luminosity and contrast throughout the image using illumination

III. PROPOSED SYSTEM

An algorithm for retina image classification without the need for prior segmentation of suspicious lesions was developed. Manual lesion segmentation is time consuming and automatic segmentation algorithms might not be accurate, thus removing the need for lesion segmentation can make the classification more robust. The algorithm is mainly based on the texture analysis of the retina background by means of LBP and Probabilistic Neural Network.

A. Pre-Processing

Due to the fact that the images under study belong to different databases, the size of the images varies. As the LBP and VAR values depend on the radius of the neighbourhood, the images must be resized to a standardized size to obtain comparable texture descriptors. The images are resized using the length of the horizontal diameter of the fundus as reference. Bicubic interpolation is used for resizing, the output pixel value is a weighted average of pixels in the nearest 4-by-4 neighbourhood. Before feature extraction, a median filter for noise reduction is performed using a 3-by-3 neighbourhood.

Only the pixels of the retina background are considered significant for the texture analysis. Thus the main structures of the fundus (the vascular network and the optic disc), which are not related to the diseases under study, should not be taken into account when the fundus texture is analysed. Some preliminary tests showed that if these predominant structures were included in the texture analysis, the differences between healthy and pathological images were not appreciated due to the similar aspect of these structures.

Median filtering is a non-linear operation often used to reduce salt and pepper noise and preserve edges. This process is performed on the 3 components of the image such as Red, Green, Blue.

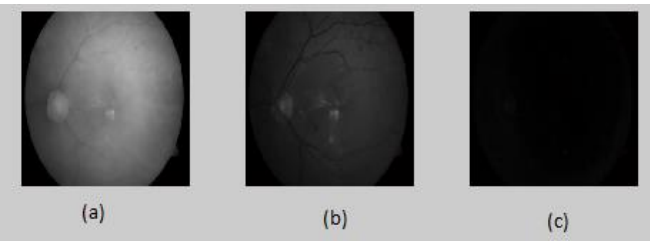


Fig 2. Median Filtering on R,G and B components, respectively (a,b,c)

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

B. Feature Extraction

The LBP and VAR operators are used to characterize the texture of the retina background.

i. Local Binary Pattern

Local binary patterns (LBP) are a powerful grey-scale texture operator used in many computer vision applications because of its computation simplicity. The first step in LBP is to produce a label for each pixel in the image where the label is found based on the local neighbourhood of the pixel which is defined by a radius, R, and a number of points, P. The neighboring pixels are thresholded with respect to the grey value of the central pixel of the neighbourhood generating a binary string or, in other words, a binary pattern. The value of a LBP label is obtained for every pixel by summing the binary string weighted with powers of two as follows:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)\cdot 2^P, \quad s(x) = \begin{cases} 1 \; if \; x \geq 0 \\ 1 \; if \; x < 0 \end{cases} \quad (1)$$

where g_p and g_c are the grey values of the neighbourhood and central pixel, respectively. P represents the number of samples on the symmetric circular neighbourhood of radius R.

The g_p values are interpolated to fit with a given R and P. The values of the labels depend on the size of the neighbourhood (P). 2^P different binary patterns can be generated in each neighbourhood. However, the bits of these patterns must be rotated to the minimum value to achieve a rotation invariant pattern. In the case of $P = 8$, only 36 of the 2^P possible patterns are rotation invariant, i.e., $LBP_{8,R}$ can have 36 different values. Figure 3 shows how LBP are calculated for a circular neighbourhood of radius 1 ($R = 1$) and 8 samples ($P = 8$).

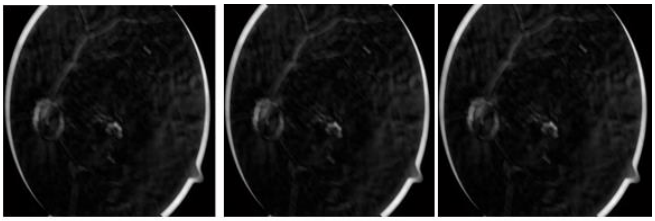
When LBP are used for texture description, it is common to
include a contrast measure by defining the rotational invariant
local variance as follows:

$$VAR_{P,R} = \frac{1}{P}\sum_{p=0}^{P-1}(g_p - \mu)^2, \; \mu = \frac{1}{P}\sum_{p=0}^{P-1} g_p. \quad (2)$$

The LBP and VAR measures are complementary and are combined to enhance the performance of the LBP operator [1]. LBP and VAR operators are calculated for each pixel of the RGB images using $P = 8$ and the values of $R = \{1,2,3,5\}$.

(a) (b) (c)

Fig 3. Feature extraction using P = 8 and R = 5, LBP images calculated on R , G and B components, respectively (a,b,c)



(a) (b) (c)

Fig 3. Feature extraction using P = 8 and R = 5, VAR images calculated on R , G and B components, respectively (a,b,c)

Masking is the process of setting pixel values in an image to zero or some other value. Masking can be done in two ways such as using an image as mask or setting image where some of the pixel intensity values are zero or non-zero. After masking the optic disc and vessel segments, the LBP and VAR values within the external mask of the fundus are collected into histograms, one for each color (RGB).

(a) (b) (c)

Fig: 4. LBP masking on R , G and B components, espectively (a,b,c)

Different statistical information is extracted from these histograms to use it as features in the classification stage. Concretely, the calculated statistical values are: mean, standard deviation, median, entropy, skewness and kurtosis. To sum up, 6 statistical values are calculated from each LBP and VAR histogram, giving place to 12 features for each radius used[14]. Consequently, the total number of features is equal to 144 (12 features x 4 radius x 3 components).

C. Classification

Probabilistic Neural Network (PNN) is used for the classification. PNN is a feed forward neural network, which was derived from the bayesian network. It has many advantages such as fast training process and training samples can be added or removed without extensive retraining, In PNN, the operations are organized into a multilayered feed forward network with four layers such as input layer, pattern layer, summation layer and output layer.

Classification is performed on the basis of the weight prediction. It generates output by comparing the weighted votes for each target category accumulated in the pattern layer
and uses the largest vote to predict the result. PNN has many advantages such as its training process is fast and it does not generate any local minima issues and the training samples can be added or removed.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

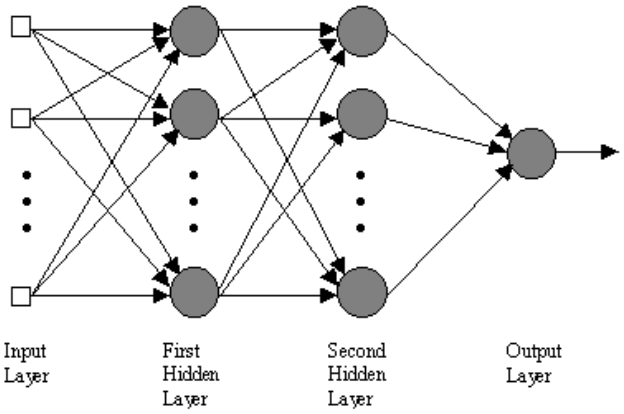


Fig 5. Architecture of Probabilistic Neural Network

IV. Experimental Evaluation

Matlab is used to implement the proposed technique using PNN. The data set used is DRIVE and it comprise of the set of 40 images. It is divided into a training set and testing set, both containing 20 fundus images. Performance of the classifier is evaluated by using several parameters such as True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) are calculated. The parameters are calculated by comparing the classifier outcome with the number of normal and abnormal images from the database. For an abnormal image, the result is true positive if the outcome of classification is abnormal and the result is False Negative (FN) if the classifier output is normal. For normal image, the result is True Negative (TN), if the classifier output is normal and False Positive (FP) if the classification outcome is abnormal. In a given image dataset, these parameters, TP,TN, FP, FN are used in the calculation of the accuracy, Sensitivity (SN) and specificity (SP). Performance of the classifier can be measured in terms of sensitivity, specificity and accuracy.

Sensitivity is measure of the percentage of abnormal images classified as abnormal. Specificity is the measure of normal images that are classified correctly as normal. Accuracy is the measure of total number of well classified normal and abnormal images.

Sensitivity = TP/(TP+FN)
Specificity = TN / (TN+FP)
Accuracy = (TP+TN)/ (TP+FN+TN+FP)

The performance of the algorithms was evaluated based on two concepts: sensitivity or true positive rate (TPR) and specificity or true negative rate (TNR).

Table 1: Sensitivity and Specificity

Image	TP	TN	FP	FN	TPR	TNR	Accuracy
5	3	1	1	0	0.75	1	0.8
10	8	1	1	0	0.89	1	0.9
15	11	1	2	1	0.92	0.67	0.87
20	15	1	3	1	0.94	0.75	0.9

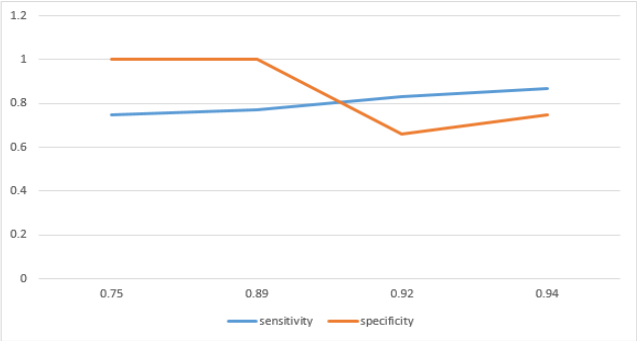


Fig. 7 Sensitivity and Specificity graph

Sensitivity, specificity and accuracy are tabulated in Table 1. The performance of the classifier is evaluated in the graph and by using this it attains 0.94 sensitivity and 0.75 specificity.

V. Conclusion

In this paper, a new approach for DR diagnosis was presented. It is based on analysing texture discrimination capabilities in fundus images to differentiate healthy patients from DR images. The most important finding is that the proposed method is capable of discriminating the classes based on analysing the texture of the retina background, avoiding previous segmentation of retinal lesions that might be time consuming and potential inaccurate, thus avoiding the segmentation is beneficial. The obtained results demonstrate that using LBP as texture descriptor for fundus images provides useful features for retinal disease screening. The Probabilistic neural network can be trained to recognize different features on a fundus image of diabetic retinopathy. The system can screen fundus with retinopathy with better accuracy and is potentially a powerful tool for the screening of diabetic retinopathy.

Acknowledgment

We are greatly indebted to our principal, Dr. JAYAMOHAN J, Dr. V. GOPAKUMAR, Professor, Head of the Department of Computer Science and Engineering, Mrs. Seena Thomas, Assistant Professor, Department of Computer Science and Engineering, LBS Institute of Technology for Women who have been instrumental in keeping my confidence level high and for being supportive in the successful completion of this paper. We would also extend our gratefulness to all the staff members in the Department; also thank all my friends and well-wishers who greatly helped me in my endeavor. Above all, we thank the Almighty God for the support, guidance and blessings bestowed on us, which made it a success.

References

1. Sandra Morales, Kjersti Engan, Valery Naranjo and Adri´an ColomerT. “Retinal Disease Screening through
2. Local Binary Patterns” IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 00, NO. 00, 2015
3. Frdric Zana and Jean-Claude Klein ,Segmentation of Vessel-Like Patterns Using Mathematical Morphology and Curvature Evaluation IEEE Transactions On Image Processing, Vol. 10, No.7, July 2001

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

4. Keith A. Goatman, Alan D. Fleming, Sam Philip, Graeme J.Williams, John A. Olson and Peter F. Sharp, Detection of New Vessels on the Optic Disc Using Retinal Photographs, IEEE Transactions on Medical Imaging, Vol. 30, No. 4, pp. 972 979, 2011.
5. E. Ricci and R. Perfetti, Retinal blood vessel segmentation using line operators and support vector classification, IEEE Trans. Med. Imag., vol. 26, no. 10, pp. 13571365, Oct. 2007
6. E. Ricci and R. Perfetti, Retinal blood vessel segmentation using line operators and support vector classification, IEEE Trans. Med. Imag., vol. 26, no. 10, pp. 3571365, Oct. 2007
7. T. Walter, J.C. Klein, P. Massin, and A. Erginay, A contribution of image processing to the diagnosis of diabetic retinopathy-detection of exudates in colour fundus images of the human retina , IEEE Transactions on Medical Imaging , Vol. 22(10),pp. 1236 1243, 2002.
8. Jo£o V. B. Soares, Jorge J. G. Leandro, Roberto M. Cesar Jr.,Herbert F. Jelinek, and Michael J. Cree, Retinal Vessel Segmentation Using the 2-D Gabor Wavelet and supervised Classification IEEE TRANSACTIONS ON MEDICALIMAGING, VOL. 25, NO. 9, SEPTEMBER 2006
9. World Health Organization (WHO), Universal eye health: a global action plan 2014-2019, 2013.
10. T. Ojala, M. Pietikinen, and T. Menp, A generalized local binary pattern operator for multiresolution gray scale and rotation invariant texture classification, in Advances in Pattern Recognition, 2nd International Conference on, 2001, pp. 397406.
11. T. Ojala, M. Pietikainen, and T. Maenpaa, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 24, no. 7, pp. 971987, 2002.
12. M. Heikkil, M. Pietikinen, and C. Schmid, Description of interest regions with local binary patterns, Pattern Recognition, vol. 42, no. 3, pp. 425 436, 2009.
13. Z. Yang and H. Ai, Demographic classification with local binary patterns, in Advances in Biometrics, ser. Lecture Notes in Computer Science, S.-W. Lee and S. Li, Eds., 2007, vol. 4642, pp. 464473.
14. L. Nanni, A. Lumini, and S. Brahnam, Local binary patterns variants as texture descriptors for medical image analysis, Artificial Intelligence in Medicine, vol. 49, no. 2, pp. 117 125, 2010.
15. M. Mookiah, U. R. Acharya, R. J. Martis, C. K. Chua, C. Lim, E. Ng, and A. Laude, Evolutionary algorithm based classifier parameter tuning for automatic diabetic retinopathy grading: A hybrid feature extraction approach, Knowledge-Based Systems, vol. 39, no. 0, pp. 9 22, 2013.
16. M. M. R. Krishnan and A. Laude, An integrated diabetic retinopathy index for the diagnosis of retinopathy using digital fundus image features, Journal of Medical Imaging and Health Informatics, vol. 3, no. 2, pp. 306313, 2013.

Anila V M, is M.Tech Student in the Department of Computer Science and Engineering, Lal Bahadur Shastri Institute And Technology for Women , Trivandrum Kerala.

Seena Thomas, is assistant professor in the Department of Information Technology, Lal Bahadur Shastri Institute And Technology for Women , Trivandrum Kerala.

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)