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Automatic Screening and Classification of Diabetic Retinopathy

Shrutika Patil[1], Prof. Mrs. Manjiri Gogate[2]
[1, 2]Electronics and Telecommunication Engineering, Mumbai University, Mira Road (E), Maharashtra, India-401107

Abstract— *Diabetic Retinopathy (DR) is a microvascular complications caused by increase of insulin in blood, leading to blindness or vision loss because of changes in blood vessels of retina. DR is highly preventable with regular screening and timely intervention of lesions which can help ophthalmologists in detecting at an early stage. The background or non-proliferative DR contains four types of lesions, i.e. microaneurysms, hemorrhages, hard exudates and soft exudates. This paper presents a novel automatic approach for detecting DR in eye fundus images by employing image processing techniques. The proposed system consists of preprocessing, feature extraction using Gray Level Co-Occurrence Matrix (GLCM), and classification is done using Support Vector Machine (SVM) and k Nearest Neighbor (kNN). The proposed system uses genetic algorithm to evaluate and test publicly available retinal image database using performance parameters such as sensitivity, specificity and accuracy.*

Keywords— *Diabetic Retinopathy, Gray Level Co-Occurance Matrix, Support Vector Machine, k-nearest neighbor.*

I. INTRODUCTION

Diabetic Retinopathy is a microvascular complication caused by diabetes mellitus leading to damage in retina. It is a major cause of blindness in middle and advanced age group [1]. According to Diabetes Information Data, from total of 20.8 million people suffers from diabetes but only 14.6 million are diagnosed. DR is a progressive disease, i.e. the patient does not feel any change at early stage in his vision but when he feels it has already reached to its advance stage. Thus early detection of DR is necessary to prevent vision loss, which is done by regular screening and timely intervention of lesions that helps ophthalmologists in detection using eye fundus images. Digital eye fundus images used for automated diagnosis of DR are acquired using fundus cameras.

DR is broadly classified in to two stages: Non Proliferative DR (NPDR) and Proliferative DR (PDR). NPDR contains four types of lesions namely microaneurysm (MA), Hemorrhages (HM), Hard Exudates (EX), and cotton wool spots(CWS) also called soft exudates. These are caused due to any changes in components of retina like blood vessels, fovea, macula and optic disc. Microaneurysms are small chambers like structure caused by local distension of capillary walls and are visible as small red dots [1]. Hemorrhages are huge blood clots that occurs into retina. MAs and HMs are termed as red lesions. While the bright lesions are EX and CWS that are deposited as bright yellowish patches of varying shapes and size.

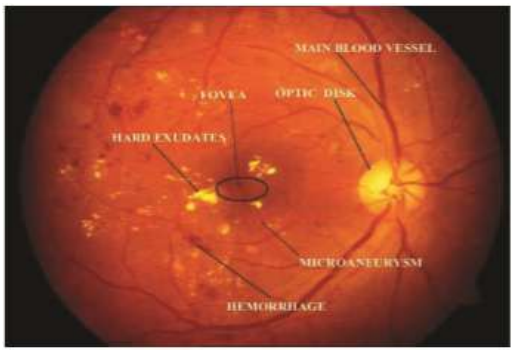

Fig. 1. Retinal abnormalities.

This is shown in fig. 1. PDR is an advanced stage of DR in which new abnormal blood vessels start growing in different regions of retina and may cause total blindness.

II. PROPOSED SYSTEM

System based on digital image processing and machine learning are playing vital role in biomedical research nowadays. Computer aided diagnostic systems have brought new horizons in detection and treatment of many common diseases [2]. Here, initially color normalization and optic disc removal is carried out using histogram processing technique. Color normalized images are further used in order to extract certain features like color and texture which are extracted with the help of Gray Level Co-occurrence Matrix (GLCM) method. Finally, feature classification is done using SVM and kNN to detect normal and abnormal images. The basic block diagram showing flow of analysis of DR symptom is shown in fig. 2.

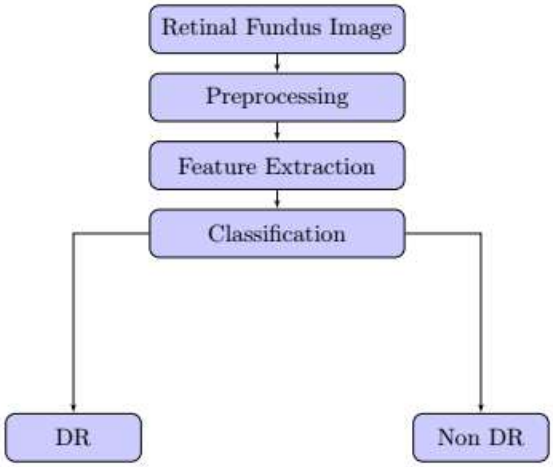

Fig. 2. Flow diagram of proposed system.

A. Preprocessing

The qualities of the retinal images obtained from database differ due to non-uniform illumination of images as well as due to some other factors such as eye movement and retinal colour variations. Hence colour normalization is necessary to

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be performed in order to make image intensity uniform. This is done using preprocessing steps which include green channel extraction, histogram equalisation, optic disc (OD) elimination and filtering.

In this paper, green channel image is taken from RGB colour image i.e. retinal fundus image ad histogram equalisation is used to adjust the intensity values of the image. The histogram equalised is then converted into binary image by applying proper thresholding value and obtaining optic disc region. Optic disc region is the bright region present in the retinal; hence can be misclassified while image analysis. hence removal of optic disc is essential before proceeding to feature extraction. Once the optic disc (OD) is removed, filtering of OD eliminated image is done to remove poor illuminated pixels.

B. Feature Extraction

In order to classify colour normalised image several features need to be extracted because image texture provides useful knowledge about the spatial arrangement of colour or intensities in normalized retinal image. In this paper, colour and texture based features are extracted using GLCM method. It is a tabulation of how often different combinations of pixel grey levels occur in an image. It determines the relation between two pixels namely reference pixel and neighbouring pixel and then calculates features depending upon the co-occurrence of the relative position of the pixel with respect to each other. The features calculated from these GLCM matrices are Correlation, Energy, Entropy, Homogeneity, Inverse Difference moment and Variance.

C. Classification

To classify the retinal images as normal or infected with the help of colour and texture based features, Support Vector Machine (SVM) and k- Nearest neighbor (kNN) classifiers are used. SVM is a supervised learning process applied for analyzing the training data to find optimal way to classify DR images into respective classes: Mild, Normal, or Severe. SVM models constructs a hyperplane for separating the given data linearly into separate classes as shown in fig. 3(a). The classification parameters are formed according to calculated features using SVM algorithm. For nonlinear classification of given data, SVM uses nonlinear kernel function to map given data into high dimensional feature space where given data can be classified linearly shown in fig 3 (b). Kernel function K(x, y) represents the inner product $<\phi(x), \phi(y)>$ in feature space [3]. Kernel function used is:

$$K(x,x') = \exp\left\{\frac{\|x-x'\|^2}{2\sigma^2}\right\} \quad (1)$$

where, x and x' are training vectors; σ is parameter that controls width of Gaussian.

In k- nearest neighbor classifier, the object is classified by a majority vote of its neighbors, with the object being assigned the most common class amongst its k-nearest neighbor. kNN allows soft classification in which each pixel is assigned a probability of it being a reference pixel. To accomplish this all k neighbors in the feature space of test pixel were examined. When n neighbors were labeled as being a reference pixel, the posterior probability that test pixel is a reference pixel itself p was determined by [8]:

$$p = \frac{n}{|k|} \quad (2)$$

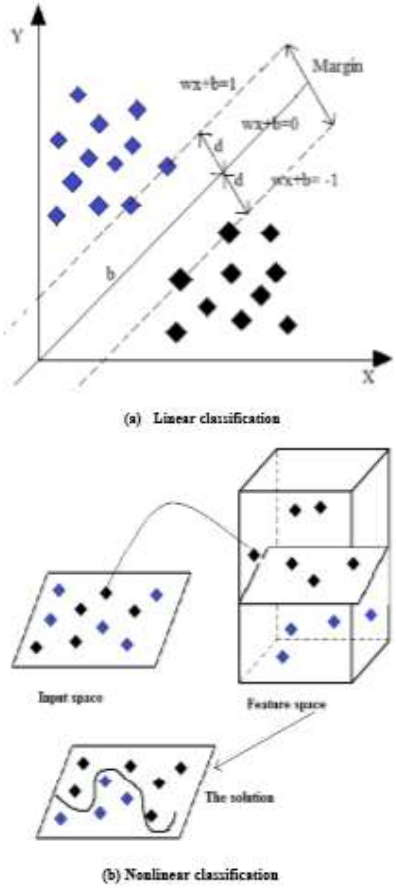

Fig. 3. SVM architecture.

III. RESULTS

In this paper, color normalization using histogram processing is used in normal fundus images in order to uniformly redistribute the intensities of images. Usually optic disc present in retinal image is misclassified as noise, so optic disc is removed using edge detection method. After optic disc elimination, GLCM features are extracted and are used by SVM and kNN classifier to detect exudates, microaneurysms and haemorrages from abnormal images.

The implementation of classification is carried out using MATLAB. The result of classifier is calculated as accuracy by formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

where, TP = True positives; TN = True negatives; FP = False positives; FN = False negatives.

Table I shows the result of percentage of accuracy for DR images using SVM and kNN classifiers.

TABLE I. Result of percentage of accuracy.

Model	SVM	kNN
Accuracy	90	80

Fig. 4 shows Grayscale images of results obtained after each stage of preprocessing.

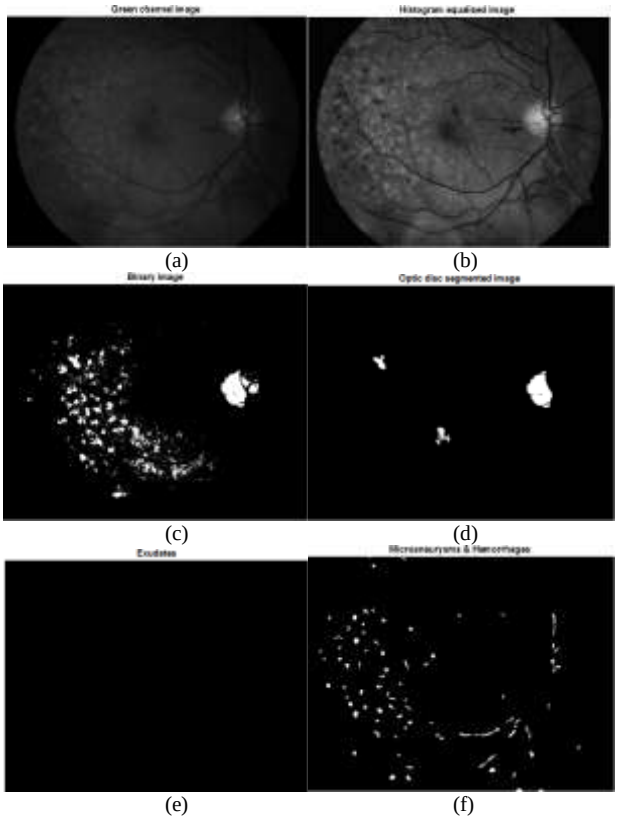

Fig. 4. (a) Green channel image (b) Histogram equalised image (c) Binary image (d) optic disc segmented image (e) Image containing only exudates (f) Image contaning only MAs and HMs

IV. Conclusion

This paper proposes an intelligent method for detecting initial lesions whose appearance characterizes as DR, a microvascular complication arising due to diabetes that is caused by fluid leaking in blood vessels. This method also intends in helping the ophthalmologists in screening the retinal images to detect symptoms as faster and more easily. Rather an ophthalmologists uses an ophthalmoscope to visualize the retina and detecting DR stages through his/her brain. Thus by regular screening of DR, evolution of DR may be avoided.

The proposed method provides with an accuracy of about 80% to 90% for both SVM and kNN classification techniques. As future work, another methods can be evolved to detect other lesions related to DR or else some other diseases that may affect retina.

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References

[1] ManojKumar S. B., Manjunath R. and H. S. Sheshadri, "Feature extraction from the fundus images for the diagnosis of Diabetic Retinopathy," *2015 International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT)*, Mandya, 2015, pp. 240-245.

[2] M. U. Akram, A. Tariq, M. A. Anjum, M. Y. Javed, "Automated Detection of Exudates in Colored Retinal Images for Diagnosis of Diabetic Retinopathy," *OSA Journal of Applied Optics*, 2012, Vol. 51, No. 20, pp. 4858-4866.

[3] Aravind C., Ponnibala M., Vijayachitra S. "Automatic detection of microaneurysms and classification of diabetic retinopathy images using SVM technique," In: *IJCA Proceedings on international conference on innovations in intelligent instrumentation, optimization and electrical sciences (ICIIIOES)*, 2013, Vol. 11, pp. 18–22

[4] K. Ram, G. D. Joshi and J. Sivaswamy, "A Successive Clutter - Rejection - Based Approach for Early Detection of Diabetic Retinopathy," *IEEE Transactions on Biomedical Engineering*, 2011, Vol. 58, No. 3, pp. 664-673.

[5] M. U. Akram, A. Tariq, S. A. Khan and S. A. Bazar, "Microaneurysm detection for early diagnosis of diabetic retinopathy," *Electronics, Computer and Computation (ICECCO), 2013 International Conference on*, Ankara, 2013, pp. 21-24.

[6] Alan D. Fleming, Sam Philip, Keith A. Goatman, John A. Olson, Peter F. Sharp "Automated microaneurysm detection using local contrast normalization and local vessel detection," *IEEE Trans. Med. Imag.*, 2006, Vol. 25, No. 9, pp. 1223–1232.

[7] B. Zhang, X. Wu, J. You, Q. Li, and F. Karray, "Detection of microaneurysms using multi-scale correlation coefficients," *Pattern Recogn*., 2010, Vol. 43, No. 6, pp. 2237– 2248.

[8] Meindert Niemeijer*, Bram van Ginneken, Joes Staal, Maria S. A. Suttorp-Schulten, and Michael D. Abràmoff, "Automatic detection of red lesions in digital color fundusphotographs," *IEEE Trans. on Med. Img*., 2005, Vol. 24, No. 5, pp. 584-592.

[9] Prakash J., Sumanthi K. "Detection and classification of microaneurysms for diabetic retinopathy," *Int J Eng Res Appl* 2013, Vol. 4, pp. 31–36.

[10] Priya R, Aruna P, Suriya R (2013) "Image analysis technique for detecting diabetic retinopathy," *Int J Comput Appl*, Vol. 1, pp. 34–38.

[11] C. Sinthanayothin, J. F. Boyce, T. H. Williamson, H. L. Cook, E. Mensah, S. Lal, and D. Usher. "Automated detection of diabetic retinopathy on digital fundus images," *Diabetic Medicine*, 2002, Vol. 19, pp. 105–112.

[12] L. Gagnon, M. Lalonde, M. Beaulieu, and M. C. Boucher, "Procedure to detect anatomical structures in optical fundus images," In *Proc. SPIE Medical Imaging: Image Processing*, 2001, pp. 1218–1225.

[13] Sopharak, A., Uyyanonvara, B., Barmanb, S., Willliamson, T. H., "Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods," *Comput. Med. Imaging Graph*, 2008, Vol. 32, No. 8, pp. 720-727.

[14] A. Osareh, B. Shadgar, and R. Markham, "A computational intelligence-based approach for detection of exudates in diabetic retinopathy images," *IEEE Trans. Inf. Technol. Biomed*., 2009, Vol. 13, pp. 535–545.

[15] 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 color fundus images of the human retina," *IEEE Trans. Med. Imag.*, 2002, Vol. 21, pp. 1236–1243.

[16] H. Yazid, H. Arof, and H. M. Isa, "Automated identification of exudates and optic disc based on inverse surface thresholding," *J. Med. Syst.*, 2012, Vol. 36, pp. 1997–2004.

[17] J. Sung, S. Y. Bang, and S. Choi, "A Bayesian network classifier and hierarchical Gabor features for handwritten numeral recognition," *Pattern Recogn. Lett.* 27, 2006, pp. 66-75.

[18] R. C. Gonzalez and R. E. Woods, "Digital Image Processing," *2*nd Edition, Prentice-Hall, 2002.

Email address: shrutika.patil25@gmail.com