



SEVERITY GRADING FOR DIABETIC RETINOPATHY

Mr.M.Naveenraj¹, K.Haripriya², N.Keerthana³, K.Mohana Priya⁴, R.Mounika⁵

^{1,2,3,4,5} Department of ECE, Kathir College of Engineering

Abstract: This paper presents the determination of severity grading of the diabetic retina to avoid permanent blindness. This paper analyses the retinal image by converting it to a grey scale image. This is the initial process done before segmenting the image. Segmenting the image involves histogram equalization and a special filter. The background of the fundus image is considered for segmenting the optic disc(OD) and vasculature and the foreground region is considered for bright and red lesions. Lesion classification involves PNN(Probabilistic Neural Network) classifier which combines the feature of GMM(Gaussian Mixture Model) and kNN(k-Nearest Neighbor). This classification produces a filtered image enhanced with red circles in red lesions and blue circles in bright lesions. Severity grading is determined by using the red and bright lesion count.

Keywords: segmentation, histogram equalization, optic disc, vasculature, bright and red lesions, lesion classification, severity grade.

I. INTRODUCTION

Diabetic retinopathy is the condition that occurs in people with diabetes and is the result of damage to tiny blood vessels that nourish the retina. They leak blood and fluids that causes swelling of retinal tissue and clouding of vision. If left untreated diabetic retinopathy can cause blindness. In the year 2015 over 7.7 million people have been affected by diabetic retinopathy. Statistics show that 60% of the patients requiring laser surgery to prevent blindness do not receive treatment [2].

The increase in feasibility of diabetic retinopathy screening have recently gained importance by computer aided screening system. For automated detection of lesions such as exudates, hemorrhages, cotton wool spots and microaneurysms several algorithms have been developed in recent years. Hard exudates means yellow flecks whose lipid residues serous leakage from damaged capillaries. Fluffy white patches on the retina are known as cotton wool spots which occur due to damage of nerve fibers. Escape of blood from the ruptured blood vessels causes bleeding which in turn increases the heart beat between systolic and diastolic blood pressure. This is known as hemorrhages which are detected with symptom of pale skin. Micro aneurysm leads to protruding of blood from artery or vein in the back of eye. These protrusions leak blood into retinal tissue. this causes vascular disease and high blood pressure. Statistics say that the number of people affected by diabetic retinopathy will increase to 14.5 million in the year of 2050. Medalytix [6], has been for screening normal patients without DR from abnormal patients with DR on a local dataset, with sensitivity in the range 97.4-99.3% on diabetic patients in Scotland. The screening outcome combined with manual analysis of the images that are classified as abnormal by the automated system has shown to reduce the clinical workload by more than 25% in Scotland [6].

The proposed system design aims at outlining three separate DR detection stages, and minimizing the run time complexity. The main contribution of this paper is to reject false positives that occur while segmentation. This method classifies the bright lesions as cotton wool spots and hard exudates and red lesions as hemorrhages and micro aneurysms. This classification is to reduce the time complexity by 18 -24%. Our aim is to find an new classifier that has high sensitivity and low computational time complexity.

II. 2.BLOCK DIAGRAM

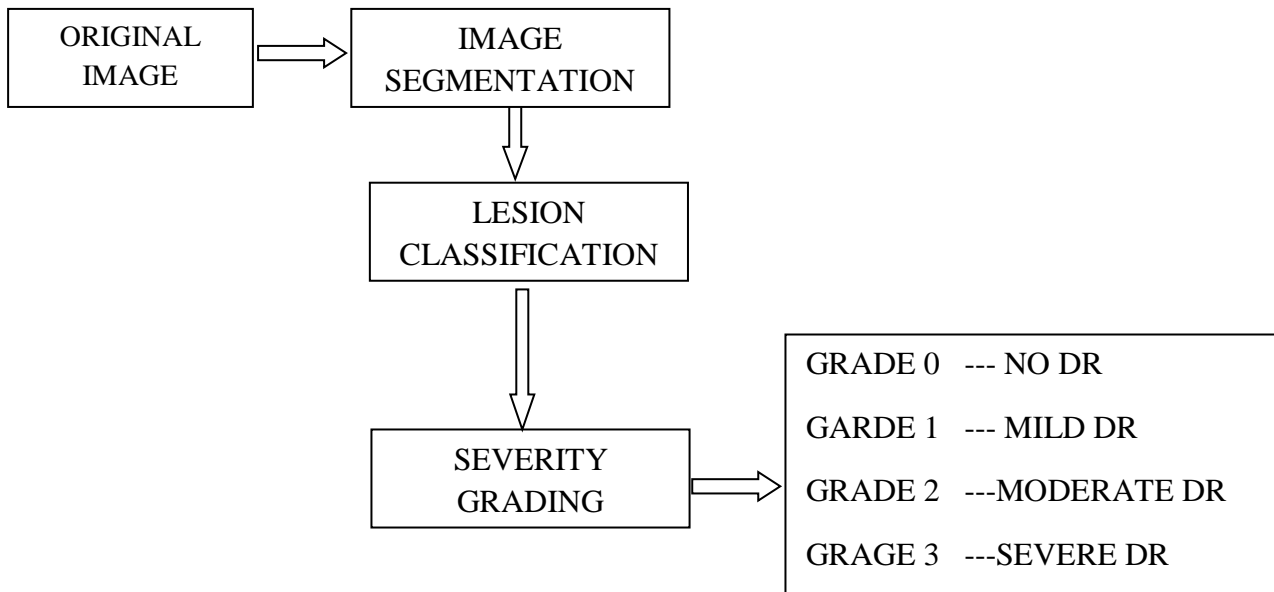


Figure.1

III. METHOD AND MATERIALS

The block diagram represents the three stage algorithm to detect and grade the DR severity using fundus image.

In stage 1, The region corresponding to the optic disc and vasculature are detected. The candidate bright and red lesions region is considered as fore- ground.

In stage 2, Classifiers are used to classify lesions from non lesion region. The bright lesions are classified into cotton wool spots and hard exudates. The red lesions are further classified into hemorrhages and micro aneurysms. Two classifiers namely GMM and kNN are used to classify the lesions[1].These classifiers are implemented in MATLAB.

In stage 3, number of bright and red lesions is counted to generate the severity grade for DR. The grade $G=0$ implies no DR, $G=1$ implies mild DR, $G=2$ implies moderate DR, $G=3$ implies severe DR.

$$HE = |U_j R_{HE}(j)|, CWS = |U_j - R_{CWS}(j)| \quad (1)$$

$$MA = |U_m R_{MA}(m)|, HA = |U_m - R_{HA}(m)| \quad (2)$$

$$\forall, G = \Psi(HE, CWS, MA, HA)$$

where, $G = \{0, 1, 2, 3\}$.

HE=Hard exudates, MA=Micro aneurysms

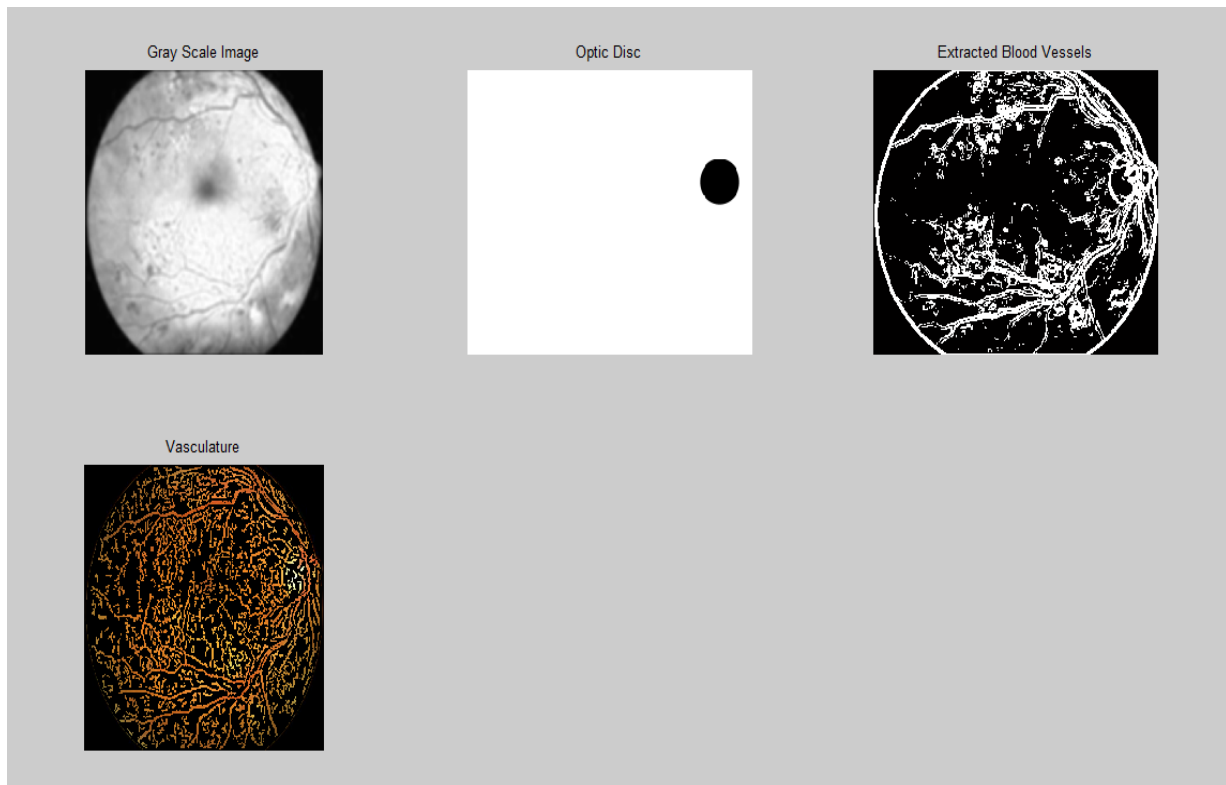
IV. PROPOSED SYSTEM

In this proposed system, three stages are involved to find the severity grading of fundus images.

4.1. Image segmentation

In this stage, the regions are masked out corresponding to optic disc and blood vasculature. Initially the image is converted into gray scale image. This is important since a bright optic disc may be mistaken as a bright lesion and the vasculature can be false detected as a red lesion. The

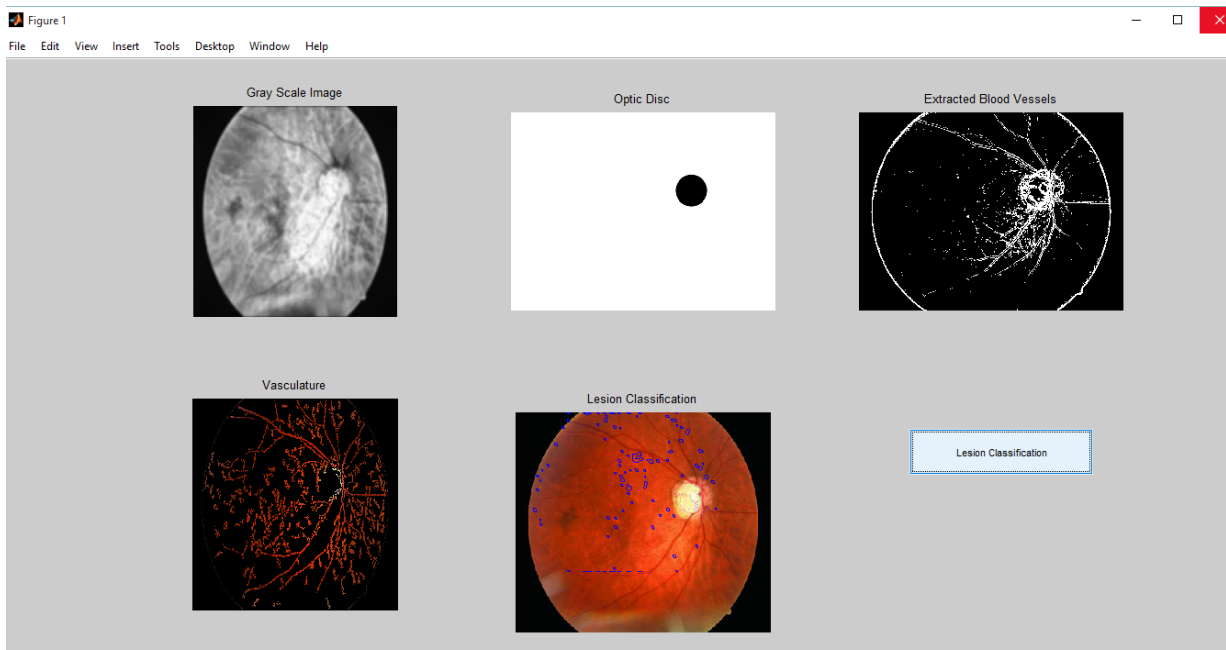
contribution of image segmentation is mainly to minimize the pixel intensity. This intensity arises due to dark pixels corresponding to thick blood vessel occurring at optic disc region.



4.2. Lesion classification

Lesion classification is mainly used to separate the red and bright lesions. This separation is done in foreground region of fundus image. In the base paper DREAM (Diabetic Retinopathy Analysis using Machine learning)[1], the author used two classifiers namely GMM(Gaussian Mixture Model) and kNN(k-Nearest Neighbor). In this paper we are using PNN (Probabilistic Neural Network) classifier which has combined features of GMM and kNN. This classification produces a filtered image enhanced with red circles in red lesions and blue circles in bright lesions.

4.3 DR severity grading



After the lesions are classified, the number of counts of bright and red lesions determines the severity grading.

Grade	Description
0	$(MA = 0)$ and $(HA = 0)$
1	$(0 < MA \leq 5)$ and $(HA = 0)$
2	$(5 < MA \leq 15)$ or $(0 < HA < 5)$
3	$(MA \geq 15)$ or $(HA \geq 5)$

The number of HA, MA, HE and Table 1 computed by using(1) and (2).lesion combination on DR severity has been studied in[11] and [12] to derive the severity grading of DR. For red lesion detection, detected lesion will result in false interpretation of the DR severity. The performance for selecting lesion classifiers is as follows,

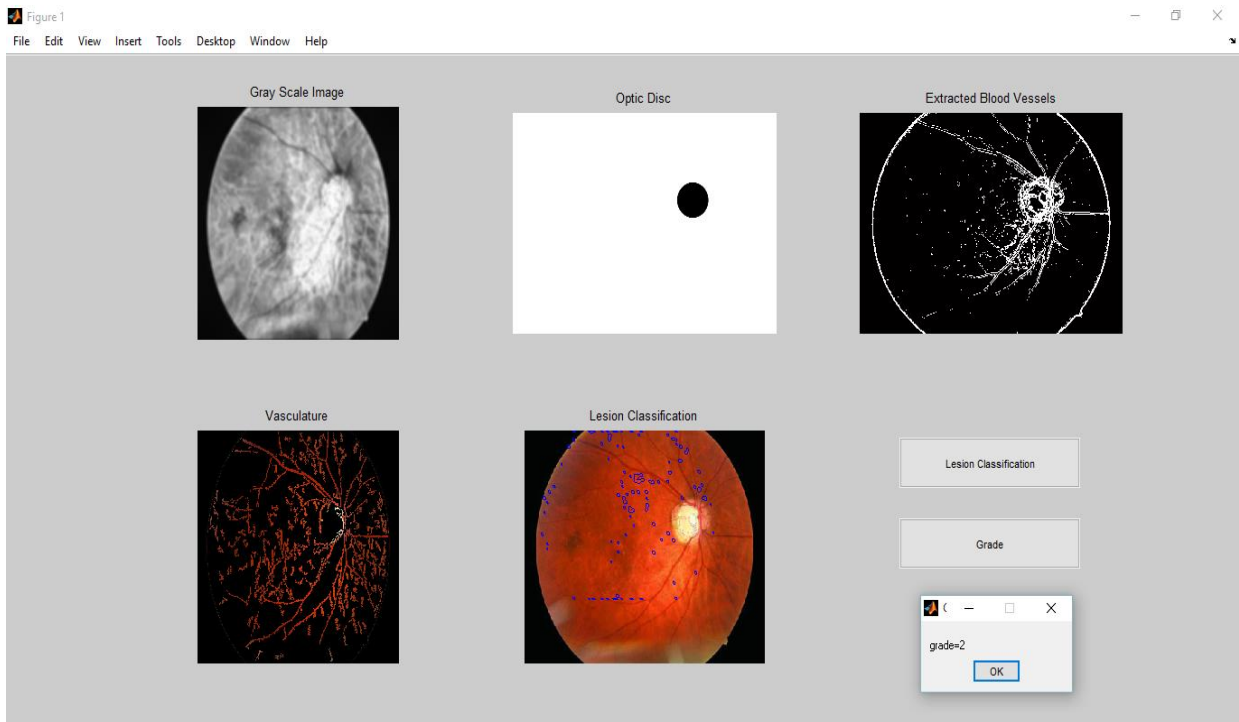
- 1) Bright lesion classifier- It must incur with high specificity or low false positives.
- 2) Red lesion classifier- It must incur with high sensitivity or low false negatives.

Table 2

GRADE	DR SEVERITY
G=0	Non proliferative DR
G=1	Mild Non proliferative DR
G=2	Moderate Non proliferative DR
G=3	Severe Non proliferative DR

V. RESULTS

The performance of three stages of DR severity grading system was analyzed individually. In the first stage of image segmentation the detection Optic Disc region plays a vital role so as to ensure



that fewer instances of false positives occur while detecting bright lesions. Analyzing the performances of second stage it classifies the lesions with low computational complexity and the third stage of the grading system was used in metrics. They are defined in terms of true positive (TP),

true negative (TN), false positive and false negative. This stage produces the grade based on the lesion count. The final goal of DR detection system is to classify the fundus image free from retinopathy lesions as normal and the classified images with bright and red lesions were abnormal. Early detection of Diabetic retinopathy will help the people to escape from permanent blindness.

VI. CONCLUSION AND DISCUSSION

In this paper we have proposed a three stage system for Diabetic retinopathy that detects and grades fundus images for severity of non proliferative DR. In this study we have used a new classifier called PNN (Probabilistic Neural Network). It is noteworthy that the first stage of grading system is an important step for correctly detecting the presence of DR. However it is possible that some fundus images with additional retinal pathologies such as, myelination or peripapillary atrophy. The entire optic disc region is not completely masked out and may result in additional bright lesion. Erroneous segmentation may lead to minor inaccuracies in lesion classification. However this classification error is significantly small. Since bright lesions are not considered for evaluating severity it will not impact the final DR severity grade produced by the system.

In this study we observe that for the red lesion classification problem, the number of negative samples are four times more than the positive samples, PNN is the best classifier. Using any other classifier will increase the complexity of the classification process. The future work will be focused on using a different algorithm for segmentation so as to simplify the segmentation process. It will reduce the time complexity and increases the sensitivity and specificity of the grading system. Additional future work can be directed towards the detection of revascularization and vascular beading caused by proliferative Diabetic retinopathy.

REFERENCES

1. Sohini Roychowdhury, "DREAM: Diabetic Retinopathy Analysis Using Machine Learning" vol 18, No.5, September 2014.
2. S.Garg and R.M.Davis, "Diabetic retinopathy screening update," Clin.Diabetes, Vol.27, no.4, pp.140-145, 2009.
3. M.D.Abramoff, M. Niemeijer, and S.R.Russell, "Automated detection of diabetic retinopathy: Barriers to translation into clinical practice," *Expert Rev.med.Devices*, vol.7, no.2, pp. 287-296, 2010.
4. A.Osareh, M. Mirmehdi, B. Thomas, and R.Markham, "Classification and localisation of diabetic-related eye disease," in *Proc.Computer vision Eur.Conf.Comput.vis.*, 2006, vol.2553, pp. 325-329.
5. C. Agurto, V. Murray, E. Barriga, S. Murillo, M. Pattichis, H. Davis, S. Russell, M. Abramoff, and P. Soliz, "Multiscale AM-FM methods for diabetic retinopathy lesion detection," *IEEE Trans. Med. Imag.*, vol. 29, no. 2, pp. 502-512, Feb. 2010.
6. G. S. Scotland, P. McNamee, A. D. Fleming, K. A. Goatman, S. Philip, G.J. Prescott, P. F. Sharp, G. J. Williams, W. Wykes, G. P. Leese, and J.A. Olson, "Costs and consequences of automated algorithms versus Detail.pdf" *J. Ophthalmol.*, vol. 94, no. 6, pp. 712-719, 2010.
7. M. D. Abramoff, M. Niemeijer, M. S. Suttorp-Schulten, M. A. Viergever, S.R. Russell, and B. van Ginneken, "Evaluation of a system for automatic detection of diabetic retinopathy from color fundus photographs in a large population of patients with diabetes," *Diabetes Care*, vol. 31, no. 2, pp 193-198, Feb. 2008.
8. M. Niemeijer, B. van Ginneken, J. Staal, M. Suttorp-Schulten, and M. Abramoff, "Automatic detection of red lesions in digital color fundus photographs," *IEEE Trans. Med. Imag.*, vol. 24, no. 5, pp. 584-592, May 2005.
9. A. Osareh, B. Shadgar, and R. Markham, "Comparative pixel-level ex- udate recognition in colour retinal images," *Image Anal. Recognit.*, vol. 3656, pp. 894-902, 2005.
10. L. Xu and S. Luo, "Support vector machine based method for identifying hard exudates in retinal images," *Proc. IEEE Youth Conf. Inf., Comput. Telecommun.*, pp. 138-141, Sep. 2009.
11. M. G. Lawrence, "The accuracy of digital-video retinal imaging to screen for diabetic retinopathy: An analysis of two digital-video retinal imaging systems using standard stereoscopic seven-field photography and dilated systems using standard stereoscopic seven-field photography and dilated clinical examination as reference standards," *Trans. Amer. Ophthalmol. Soc.*, vol. 102, p. 321-340, 2004.
12. A. D. S. for the Department of Health and Ageing. (2008). "Guide- lines for the management of diabetic retinopathy," [Online]. Available: [http://www.icoph.org/downloads/Diabetic Retinopathy - Detail.pdf](http://www.icoph.org/downloads/Diabetic_Retinopathy_-_Detail.pdf)