Automatic Diagnosis of Diabetic Retinopathy from Fundus Images

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Abstract. Detection of earliest symptoms of Diabetic Retinopathy and its prevention is challenging task in medical sciences. There are main three symptoms of Diabetic Retinopathy includes; Microaneurysm (MA), Hemorrhages (HA) and Exudates. Microaneurysm is the initial stage in which small round dots appears which losses partial eyesight and it is the leading cause of Hemorrhage. Hemorrhage being the advanced stage of Microaneurysm in which blood vessels bleed and insufficient intake of nutrients and oxygen to retina may cause poor vision. This study based on diagnosis of Hemorrhages at earlier stages through machine learning algorithm. Research design include pre-processing, texture feature extraction, and classification approach (SVM), and segmentation procedure using Gray Wolf Optimization using datasets. The following data sets are used i.e. DIARTDB0, DIARTDB1 and real data which is collected from civil hospital LUMHS Jamshoro. The results achieved with SVM showed the minimum false, high accuracy achieved through manifold testing and training. The achieved results have the sensitivity of 88.12%, specificity of 77.7% and accuracy of 85.35%

Keywords: Detection Diabetic Retinopathy, SVM Classification Approach, Segmentation Techniques, Fundus Images.

1 Introduction

Diabetic Retinopathy is the degeneration of blood vessels of retina and gradually losses vision. So early detection of Diabetic Retinopathy is one of the challenging task and found in diabetic persons below 50 age. Diabetic retinopathy diagnosed at its last stage when blood vessels burst and people losses their eyesight. Microaneurysm (MAs), hemorrhages (HMs) and exudates (EXs) are the possible indications of Diabetic Retinopathy. It is observed that exudate and hemorrhage have different characteristics and author has achieved high performance in the form of sensitivity value about 98% and specificity value of 91% whereas segmentation performance obtained through Dice and Jacccard similarity indexes of 0.95. It is mandatory to get scan every six months or once a year for diabetic patients to prevent the occurrence of Diabetic Retinopathy up

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to 90% in person who have diabetes for 20 years or more [1][2]. [3][4] summarized different deep learning techniques (Like ANFIS classifier with Cuckoo, PSO and Motion Pattern
Recognition) to extract early stage of DR hemorrhage using DIARETDB2 dataset with highest sensitivity and specificity of 98.67% and 98.91% respectively. Author reviewed different image processing techniques like histogram approach along with morphological operations. [5] Emphasized on a different approach of using rotating irregular filters (i.e. Edge detection) to diagnose early stage of Diabetic Retinopathy (DR). According to author, highest sensitivity achieved using different four filters on STARE images. [6] Author has analyzed advanced classification tools for detection of hemorrhage using BBR-net (bounding box refining network) with an average IoU value that is 0.8715 compared to well-annotated bounding boxes manually. [7] had given actual cause of Diabetic Retinopathy and proposed his work in two steps i.e. Classification Phase I included dataset collection (STARE Database), pre-processing, feature selection, segmentation and Classify normal or DR images using SVM and Classification Phase II was based on segmentation to detect intensity of DR stages (Exudates and Hemorrhages) using MATLAB 7.12 with high accuracy.

2 Methodology

In this research-supervised machine, learning algorithm (SVM) classify fundus images as normal and DR images. This study covers data collection, pre-processing, feature extraction, classification using SVM, then segmentation. The segmentation techniques include threshold value and Gray Wolf Optimization to segment/extract hemorrhage part from fundus image as well elaborated through following Fig.1.

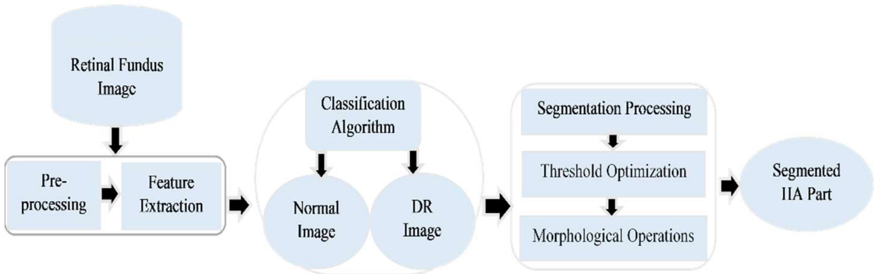


Fig. 1. Steps followed in Research Methodology

2.1 Pre-Processing

In pre-processing, converting RGB image into grayscale to make blood vessels and hemorrhage area in an image visible, and using adoptive histogram equalization to improve contrast, to get high-resolution image and reduce noise, blurring of an image. By taking fundus, images at different angle and with different resolution camera that affect image quality to resize images (to 760 by 580 pixels). On the other hand, Statistical texture features, which include mean, standard deviation, energy and contrast of the pixels to see the frequency of grayscale levels with similar values over its neighbor grayscale levels. Also locate the disease part (i; e HM) and severity of hemorrhage could be only possible through variance in grayscale levels.

2.2 Segmentation

In segmentation phase, pixel value selected using seed point, threshold value and Gray Wolf Optimization Techniques. In segmentation, gridding is applied to segment image into blocks (bs) on the basis of resemblance and each block/ spot is assigned as individual part. After gridding, selection of seed point is done to apply adoptive histogram equalization to get pixel value in segmented block. Here the pixel value is considered in between 0 and 255 as seed point in an image. After seed point, maximum accuracy obtained by applying threshold value and GWO on a segmented image.

2.3 Classification Approach

In this study, SVM used for classifying fundus image as normal or DR image. SVM that it classifies labeled data with high accuracy and equal distance of hyperplane it classifies objects with minimum chance of false detection. SVM built two hyperplanes to classify the data; linear hyperplane classifies data linearly, but in non-linear hyperplane Krnel function is used for complex data transformation in n-dimensional space. Mathematically SVM can be defined as follows;

$$min_w \lambda \left|\left|w\right|\right|^2 + \sum_{i=1}^{n}(1 - y_i\langle xi, w\rangle) + \tag{1}$$

$$\frac{\partial}{\delta w_k}\lambda\|w\|^2 = 2\lambda w_k \tag{2}$$

$$\frac{\partial}{\delta w_k}\,(1 - yi\ \langle xi, w\rangle)+ = \begin{cases} \text{o}, & \text{if} \quad y_i\langle xi, w\rangle \geq 1 \\ -\text{yi xik}, & \text{else} \end{cases} \tag{3}$$

1.1 Morphological Operations

Morphological method like erosion and dilation, opening and closing are implemented. Dilation and Erosion has been done for adding and removing pixels of low frequencies and remove the blood vessels to make Hemorrhage part more visible shown in Fig.2. In morphological method, it is only possible to make fundus image dilated and it can be more understandable using mathematical operations as represented through equations below:

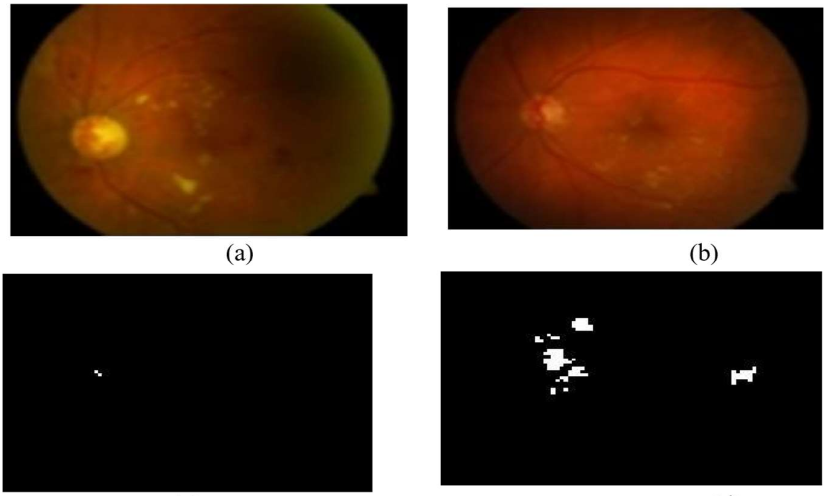
$$\text{f}\bullet\text{B} = (\text{f} \oplus \text{B})\Theta\,\text{B} \tag{4}$$

$$\text{Top} - \text{Hat (f)} = \text{f} - (\text{f} \circ \text{B}) \tag{5}$$

$$\text{f} \circ \text{B} = (\text{f}\,\Theta\,\text{B}) \oplus \text{B} \tag{6}$$

2 Database description

In this research the images of the Diabetic Retinopathy were collected from publically available data and LUMHS. Whereas for training purpose we use DIARTDb0 and DIARTB1. The testing has been done from data acquired from LUMHS. As Dataset covers the training, testing of fundus images as 80% and 20% respectively.



(a) (b) (c) (d)

Fig. 2. Segmentation of Hemorrhage part using Morphological Operations

3 Results

In this research dataset is divided in five classes so it means five times testing and training has been performed to see the high performance of Classification algorithm (SVM)with minimum false detection and achieved average results as 88.12%, 77.7%, 85.35%, sensitivity, specificity and accuracy respectively. The obtained results show high efficiency of SVM algorithm as shown in Table.1, 2 and Fig.3, 4,5.

Table 1. Average Results for Hemorrhage Detection

Sensitivity	Specificity	Accuracy
88.12%	77.7%	85.35%

Table 2. Manifold Testing Results for Hemorrhage Detection

Class	Sensitivity	Specificity	Accuracy
Test 1	86.48%	77.7%	82.9%
Test 2	88.8%	77.7%	85.36%
Test 3	84.21%	66.6%	78.04%
Test 4	84.21%	88.8%	87.8%
Test 5	96.9%	77.7%	92.68%

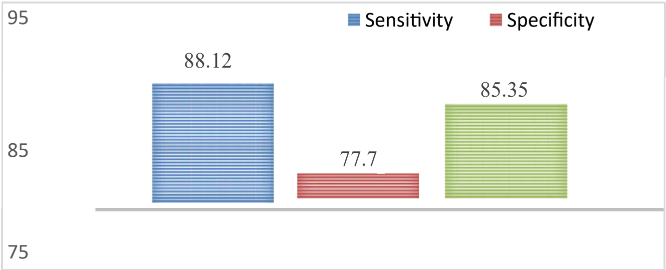


Fig. 3. Proposed Results in the form of Sensitivity, Specificity & Accuracy

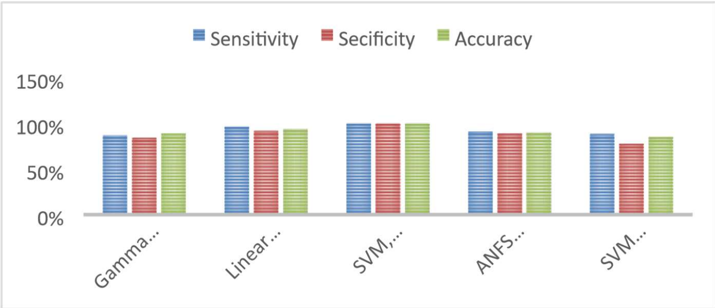


Fig. 4. Comparetive Results of the Proposed Study with Previous Work

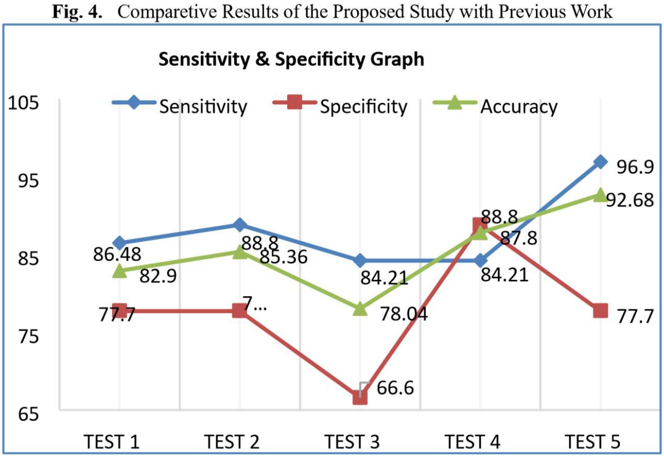


Fig. 5. Graph for manifold Testing for Hemorrhage Detection

4 Conclusion

Diabetic Retinopathy is one the alarming condition for person when he/she losses eyesight because the initial symptoms of DR are shown at early stage but are evidently become visible. This study focused on hemorrhage detection using SVM classification algorithm with morphological technique. To make automatic system more reliable and efficient statistical features have benn selected to distingush blood vessels and Hemorrhage part easily,SVM classification approach has been applied to classify normal and DR images and through segmentation similar pixel value has been considered while removing low frequency value to extract hemorrhage part from fundus image and obtained high accuracy of 85.5%. The system's efficiency can be enhanced by using advanced deep learning algorithms to overcome the chances of misclassification of DR manually.

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References

1. Sasuee Rajper, Ahsan Ahmed Ursani and Sehreen Moorat (2019). Automatic Diagnosis of Diabetic Retinopathy Using Morphological Operations. *International Journal of Sciences: Basic and Applied Research*, 48(3), pp.213–223.
2. T. Selçuk, A. Beyoğlu, and A. Alkan, "Automatic detection of exudates and hemorrhages in low-contrast color fundus images using multi semantic convolutional neural network," *Concurrency and Computation: Practice and Experience*, vol. 34, no. 6, Jan. 2022, doi: https://doi.org/10.1002/cpe.6768.
3. L. Godlin Atlas, K. P. Arjun, K. Sampath Kumar, Rajesh Kumar Dhanaraj, and A. Nayyar, "Deep learning enabled hemorrhage detection in retina with DPFE and splat segmentation in fundus images," *Biomedical Signal Processing and Control*, vol. 88, pp. 105692–105692, Feb. 2024, doi: https://doi.org/10.1016/j.bspc.2023.105692.
4. G. A. L and K. Parasuraman, "Detection of retinal hemorrhage from fundus images using ANFIS classifier and MRG segmentation," Biomedical Research, vol. 29, no. 7, 2018
5. V. Satyananda, K. V Narayanaswamy, and K. Karibasappa, "Extraction of Exudates from the Fundus Images A Review," vol. 5, no. 12, pp. 133–139, 2016.
6. Y. Huang *et al.*, "Automated Hemorrhage Detection from Coarsely Annotated Fundus Images in Diabetic Retinopathy," *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*, Jun. 2020, doi: https://doi.org/10.1109/ISBI45749.2020.9098319.
7. K. H. Babu, "Blood Vessel Segmentation in Angiograms using Fuzzy Inference System and Mathematical Morphology," vol. 2, no. 1, pp. 72–77, 2015.