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Review Article

HEMORRHAGE DETECTION AND CLASSIFICATION: A REVIEW

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ABSTRACT
Among all diseases, diabetes is a serious disease which needs some attention. Improper balance of insulin leads to diabetes. For diagnosis of such patients, we have to look for symptoms. One of the most common symptoms of diabetic person is diabetic retinopathy. Diabetic retinopathy involves changes to retinal blood vessels that can cause them to bleed or leak fluid, distorting vision. Diabetic retinopathy is the most common cause of vision loss among people with diabetes and a leading cause of blindness among working-age adults. Using image processing techniques we can detect hemorrhage using fundus images. Following paper discusses different methods for hemorrhage detection and classification.

KEYWORDS – Diabetic Retinopathy, Feature Extraction Hemorhhages, KNN, SVM

INTRODUCTION
In Diabetic retinopathy, there is damge in the tiny blood vessels in the retina. The retina is organ of our body which converts light to signal which are sensed by optic nerve to the brain. But due Diabetic retinopathy there is leak of fluid or hemorrhage (bleed) in the retina resulting in distorted vision. There are several types of damages such as hemorrhages, Microaneurysms, exudates, cotton wools etc. the effect of diabetic retinopathy. To avoid the DR, early detection is necessary.

Doctors recognize DR by diagnosing on the external visible feature like swollen blood vessel, small hemorrhages, exudates, Microaneurysms and texture of the eye. Microaneurosym and hemorrhages is the first detectable step of the DR therefore hemorrhage detection is important for early detection of DR.

The diabetic retinopathy is classified by two stages Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [1]. The diabetic retinopathy start with NPDR, firstly hemorrhage were found where the disease progress the retinal vessel blocked and blood and fluid flow through the retina and cause blindness.

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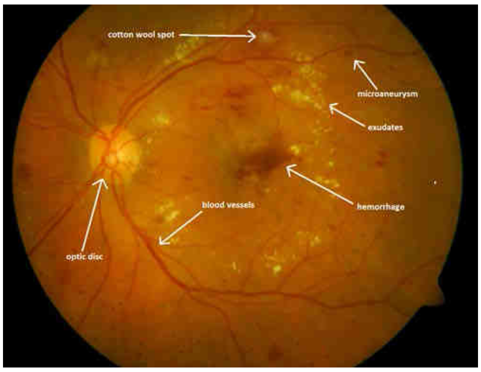

Fig. 1 Retinal image containing different types of lesion

The generalized block diagram for automatic hemorrhage detection is shown in fig. 2.

a. Database

Database collection is the first step in any system. There are various online databases for fundus image are available such as DIARETDB1, DRIVE, HRF STARE etc.

b. Preprocessing

We extract images from database to input for further processing. The color is in RGB format. We can differentiate these channels by thgere features such as bright red channel helps in detecting vascular structure, but have low contrast than green channel while blue channel is too noisy. So Reconstruction and enhancement is done by eliminating blue channel and taking the advantage of the red and green channel [2] [3].

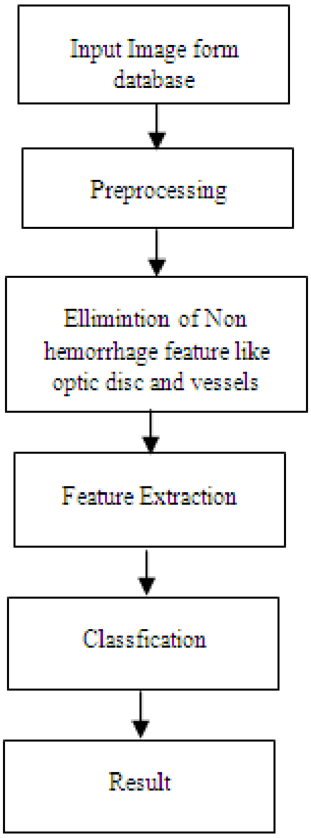

Fig. 2: Flow chart of hemorrhage detection

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c. Elimination of Non-hemorrhage Features

Images from the fundus camera are noisy and non-uniformly illuminated. We observe bright spot on the optic disc which makes hemorrhages detection difficult due to same color. So we start of with the removal of optic sic and blood vessels. This is done by adjusting brightness and contrast intensification in ROI and background [4] [5]. For this we used morphological operation.

Bae et. al. [4] in his work shows how HSV is used for correction of brighteness by processing on green channel. Then contrast enhancement is done using CLAHE technique.

Zhang and Fan [6] used multiscale morphological processing to detect spot lesion. They used scale based lesion validation to remove Vessels nad over-detection.

Matei et. al. [7] and Langroudi et. al. [8] used thresholding and morphological operation for detection of blood vessel.

Acharya et. al. [9] in there work show how we can detect hemorrhage by substracting blood vessel from affected area.

We can detect hemorrhage by removing optic disc.

Marwan and Eswaran [10] show methods to remove optic disc using median filtering from fundus image. As optic disc name suggest is a circular shape, center of the image is the key to detect optic disc. Detected optic disc is then removed by applying thresholding over median filtering.

H.A Hassan et.al [11] used iterative morphological operation for removal of optic disc. Image enhancement can be done with the help of erosion and dilation operation.

d. Feature Extraction

Feature extraction is the process which helps us find uniqueness of an object. By selecting good feature we can differentiate states and further improvement of accuracy of the result. Common feature extraction techniques are GLCM, Splat feature, etc. The detailed method is explained in following section.

- **Splat Features:**

Splat features are used to indicate the relation between its neighbor splats. Splat features are extracted by distribution and aggregation of splat based on pixel collection. Splat feature includes color, Guassian filter bank, splat extent, dog filter bank, splat area, texture, contrast, splat orientation, local texture filter, correlation, energy, and homogeneity.

- **Gray Level Co-Occurrence Matrix (GLCM):**

GLCM extract feature using texture information. It finds difference between row and column and based on the information differentiate two distinct elements. Here it uses relative frequency of two pixels which are separated by pixel distance and particular angle.

The different papers are reviewed in table 1

e. Classification

Classification is the techniques by which we gather information in the form of discrete form i.e true or false. Many techniques used to classify hemorrhages. In [2], they used features like area, aspect ratio, compactness etc. to classify the hemorrhages. In most of the research paper, hemorrhages were classified using SVM, KNN, etc techniques.

- **SVM**

SVM is very powerful and most widely used classifier. This technique is special because it gives more precise result in less time. Speed and reliability of this technique is vey higher as compare to other techniques. This technique is highly popular because it works well on nonlinear datasets also. Following analysis gives mathematics behind this technique.

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Assuming given some training data D, a set of n points in the form

$$D = \{(Xi, Yi) \mid Xi \in Rp , Yi \in \{0,1\} \}i=1 \text{ to } n \quad \ldots(3.1)$$

Where, yi is either 1 or 0, indicating the class to which the point xi belong each Xi is p - dimensional real vector.

$$W.X - b = 0 \quad \ldots (3.2)$$

Maximum - margin - hyper plane (3.2) that divides the point yi = 1 from yi = –1 in the set of points X

$$W. Xi - b \geq 1 \quad \ldots (3.3)$$

If the training data are linearly separable, hyper planes are selected by separating the data using different classes that are represented by both (3.3) & (3.4)

$$W. Xi - b \leq 1 \quad \ldots (3.4)$$

The above classifier classifies the hemorrhages into normal and hemorrhage affected retina.

- **KNN**

Another most popular classifier is KNN (K nearest neighbor) algorithm. This techniques comapres data with nearest data to make classification. Distance between the datapoint is crucial in this technique. Datapoints between training and testing data are iteratively modified to give the appropriate results. The Minkowski and Euclidean distance are usually used.

The nearest neighbor is represented by k. In [13] the value of k is selected as 101 for better accuracy. In [14] author chooses a set of 20 images are taken from a DRIVE database for training and 1200 images from MESSIDOR database [15]

- **Neural Network**

Neural Network is the oldest and most powerful technique used for classification. It the modeled as replica of human brain. It is also called as artificial neural network (ANN). Few popular method of neural network are backpropagation, feedforward network, RBF (Radial basis function), LVQ (Linear vector quantization), SOM (Self Organizing Map), etc. Architecture of neural network is the key to that helps in getting accuarate results.

Architecture of neural network consist of three layers i.e. Input layer, hidden layer and the output layer. Key parameter are weight of the system which used for determination of probability to detect correct output. Feedback network is used to improve the errors in the system. This process is persistent until getting the expected output .

D. Usher et al. [16] used neural network for classification of microneurosysm. It uses 500 images for training purpose, while 773 images were tested using ANN.

Learning vector quantization approach for hemorrhage classification is proposed by M. Garcia [17]. Small 32×32 window is used for feature extraction. 29 features were extracted and were trained and testing using MLP. 50 images were used for testing.

The Comparative analysis of different methods is tabulated below in Table I

Conclusion

Complexity of system to detect hemorrhage is increases because of confusing component present in the fundus images like blood vessels, microneurysms, fovea, optic disc which give similar results. In this paper, we reviewed existing hemorrhage detection methods so that based on this method researcher can implement a better hemorrhage detection system.

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Table 1. Comparative Analysis of different methods

Author	Technique	Database Used	Features	Classifier	Results	Advantage
Malay Kishore Dutta et al. [18]	Region Based Detection	-	Area	-	It gives good result for classifying Non-Proliferative Diabetic retinopathy	It have good accuracy, avoids redundancy in computation.
Saumitra Kumar Kuri et al. [19]	Gabor Filter with Local Entropy Thresholding	DRIVE	Local entropy using GLCM	-	It gives 97.72% accuracy and 98.15% sensitivity respectively	It have maximum true positive rate and reduce false vessels detection in fundus
Syna Sreng et al. [20]	Vessels Elimination and Noise Elimination	fundus images fromBhumibol Adulyadej Hospital	Color	-	It gives good accuracy and preciseness.	Technique used to eliminate MA (microaneurysms) and certain small noise.
Asra Ashraf et al. [21]	Retinal Whitening	Own database from AFIO Hospital Rawalpindi	discriminating features	SVM	It is a novel method for automated diagnosis of malarial retinopathy by detecting retinal whitening, cotton wool spots and Hemorrhages cases.	It gives good accuracy, sensitivity and specificity.
Jaykurnar Lachure et al [22]	Morphological Operations and Machine Learning (SVM and KNN classifier)	Messidor, DB-dataset	GLCM and Structural features		The method detect both exudates and microaneurysms. The SVM gives better performance over KNN classifier.	As combined dataset our specificity is 100% and sensitivity is more than 90% for SVM
Malay Kishore	Edge Based Method &				The combination of these approaches	This method have better accuracy

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Dutta et. Al. [18]	Strategic Thresholding				based on threshold and edge detection helps in eliminating all possible types of noises leading to false exudates that may have crept in.	without compromising the computational time.
T. Ruba et al. [23]	classifier	MESSIDIOR		SVM	It gives good Correctness, Sensitivity, and Specificity.	This method is automated and simple, it detects symptoms faster. It works effectively even on a poor computing system
Amol Bhatkar[24]	Discrete Cosine Transform (DCT)	DIARETDB0	Entropy, mean, standard deviation, average, Euler number, contrast, correlation, energy and homogeneity	MLPNN	Detecting accuracy is 100%	Classification accuracy of multi layer perceptro is Good.
Vijay Mane, Ramish B Kawadiwale, D. V. Jadhav[25]	Local entropy thresholding, Length filtering	DIARETDB1	Area, aspect ratio, eccentricity, mean intensity, standard deviation, major axis, minor axis , compactness, equavalet diameter, roundness	SVM	Sensitivity is 96.42%, specificity is 100%, Accuracy is 96.62%	The proposed method performs very well in detecting red lesions as compared to existing methods
Syna Sreng, Noppadol Maneerat, Don	Maximum entropy thresholding method,	-	Area, radius,		The result from the ophthalmologist shows that 90 % of HEs detections were	Given a success rate of 90 % with the average of processing time is 6.23 seconds

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Isarakorn [26]	median filtering, contrast limited adaptive histogram equalization, otsu thresholding,				successful with the average of processing time is 6.23 seconds per image.	per image on HEs detection, the proposed method is about to reach the requirement for the real practical software in hospital
Priyakshi Bharali, Jyoti Prakash Medhi and Dr. S.R. Nirmala [27]	CLAHE, median and average filtering, Region growing, Niblack's thresholding,	HRF, DIARETDB0, DIARETDB1, MESSIDOR			The algorithm detected hemorrhages in 551 images out of 561 images giving an accuracy of 98.22%	The experimental results show that the detection of hemorrhages is sufficiently accurate and effective. Hence this method may be used for automatic analysis of retinal diseases.
K. Udaya Bhaskar [28]	Luminosity Contrast normalization pre-processing,	DIARET DB1 & DB0 database	Mean of blue channel, mean of green channel, standard deviation of red channel, Standard deviation of blue channel, Mean of green channel intensity, Mean of blue channel, Region centroid in blue channel, Region centroid in blue	Multi-Layered Perceptron (MLP), Radial Basis Function (RBF) and FLANN classifier	Propose method having sensitivity of 99%, specificity of 89%, accuracy of 94.7%,	FLANN classifier has a advantage over MLP and RBF because FLANN does ot have any hidden layer

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			channel, Color difference of the Red channel, Color difference of the green channel, Color difference of the blue channel, Region compactness , Homogeneity			
Ishita De, Suchismita Das, Debalina Ghosh [29]	CLAHE				Proposed method gives Specificity 97.68 %, Sensivity 70%, Accuaracy 95.42 %	The method is quite good in terms of time requirement. The time taken for an image in the Drive database is less than a minute. The time required is less because we use less number of steps. Another advantage of the method is that it does not require the border masks provided in the database. So it can be used for other retinal image databases for which the border masks are not provided.
Liu Hongying , Fang Juan, Li Qingli [30]	AAV2-EPO, MHIS (hyperspectral imaging		Hyper spectral image		The experimental data indicates that the performance of	the thickness of the outer nuclear layer, comparing the relative error of the spectrum

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	system), AOTF(Acousto-optic tunable Filters),				retinal ONL cells of DR rats can return to normal levels after AAV2-EPO middle dose and high dose treatment, while AAV2-EPO low dose treatment can't effectively restore the performance of retinal ONL cells of DR rats.	and spectral similarity comparison. which helps us to confirm which group of E1□E2□E3 have optimal therapeutic effect.
Jaykumar Lachure, A.V. Deorankar, Sagar Lachure, Miss. Swati Gupta, Romit Jadhav [31]	Canny edge detector, GLCM, multiclass formulation	Messidor, DB-rect dataset,	Stuctural features, area, local maxima,red spot, energy, contrast, entropy, homogeneity, Euclidian distance	SVM, KNN	specificity is 100% and sensitivity is more than 90% for SVM.	Proposed method shows SVM classifier is better classifier than KNN. So from the extracted feature it directly concludes the disease grad as normal, moderate and severe.
Surbhi Sangwan, Vishal Sharma, Misha Kakkar [32]	Gradient magnitude segmentation, fuzzy c clustering,		Mean, sum of ON pixels, area of exudates, edge,	SVM	This paper provides a basis of classification of Normal, NPDR or PDR affected eye with high accuracy percentage of 92.6%.	These results strengthen the idea that SVM can be used efficiently and efficiently as a classifier for detecting eye related diseases causes by diabetic

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