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A Survey on Usage of Data Mining Techniques in the Detection of Hemorrhages in Fundus Images

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Abstract— Diabetes is a chronic end organ disease that occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. At last, diabetes affects the circulatory system, including the retina. Diabetic retinopathy is a disease in which the blood vessels in the retina changes or sometimes these vessels swell and leak fluid. Ophthalmologists recognize diabetic retinopathy is based on features, such as exudates, blood vessel area, microaneurysms, hemorrhages and texture. The severity of the disease is identified using number and shape of hemorrhages. Early detection of hemorrhage can help to reduce the loss of eye sight. In this paper we review data mining techniques and algorithms used for the detection of hemorrhage from retinal fundus images.

Keywords— Diabetic Retinopathy, Retinal fundus images, Medical Mining, Hemorrhages, Medical Imaging

I. INTRODUCTION

Diabetic Retinopathy (DR) is a sight threatening disease due to diabetes mellitus that affects the retina. There are five stages to indicate the severity of DR, namely no DR, mild Non-Proliferative Diabetic Retinopathy (NPDR), moderate NPDR, severe NPDR and Proliferative Diabetic Retinopathy (PDR). At first, the people suffering with DR may not show any symptoms or changes in their vision. DR is a silent disease, because it does not exhibit any symptoms until it get hard. The severity of the disease depends upon the duration of diabetes. It could get worse over the years and threaten their eye sight [1]. So far, the most effective treatment for DR can be administered only in the first stages of the disease. Hemorrhages and Microaneurysms are the first clinically observable lesions that indicate diabetic retinopathy. Therefore, their detection is very important for a diabetic retinopathy screening system. With a large number of patients, the number of ophthalmologists is not sufficient to cope with all patients, especially in rural areas. Early detection of DR through screening can prevent blindness and allow for maintenance of good vision [2]. A typical screening process involves the acquisition of retinal images from the patient followed by manual examination of each individual image by medical experts (these are actually often technicians trained by medics) in order to identify any signs of deterioration. This process is known to be expensive, inefficient and time consuming. These few reasons alone make the development of an automated system imperative [3]. Therefore, automated early detection could limit the severity of the disease and assist ophthalmologists in investigating and treating the disease more efficiently. The typical features of diabetic retinopathy are microaneurysms, small intra retinal dot hemorrhages, larger blot hemorrhages, all of which are red lesions, and whitish lesions for example lipid exudates, and cotton wool spots which are nerve fiber layer micro infarcts. With an increasing diabetic population and the need for quality assurance pathways, it is not surprising that considerable effort has been spent over the past 10–15 years on investigating whether these lesions could be detected by computer aided pattern recognition algorithms [4]. Diabetic Retinopathy affected fundus image is shown in the figure 1.The objectives of this paper are to review the relevant literatures in the field of hemorrhage detection, to provide researchers with a detailed resource of retinal images, to conclude the available methodologies used for detection of hemorrhage.

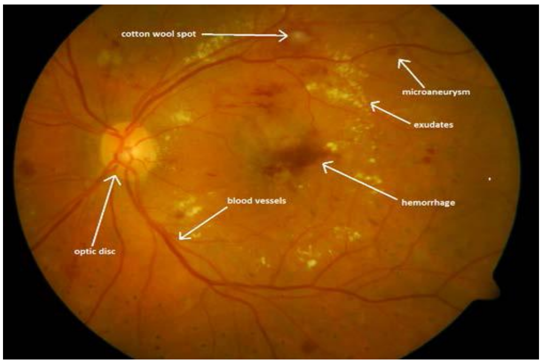

Fig 1 Diabetic Retinopathy affected retinal fundus image

II. TECHNIQUES USED IN HEMORRHAGE DETECTION

Most of the methods of hemorrhage detection can be divided into 2 consequent levels: red lesion candidate extraction and classification. First level is image pre-processing to reduce noise and improve contrast, then the red area of the picture are extracted and segmented to be the candidate of red lesion. The vessel segmentation algorithms are used for blood vessel extraction from the candidates to reduce false detection. Then the feature analysis that involves feature extraction and feature selection is used for hemorrhage detection. The classification algorithm is applied to categorize these features into the hemorrhage group (abnormal) and not hemorrhage group (normal). Overall processes for detection of hemorrhages are concluded in figure 2.

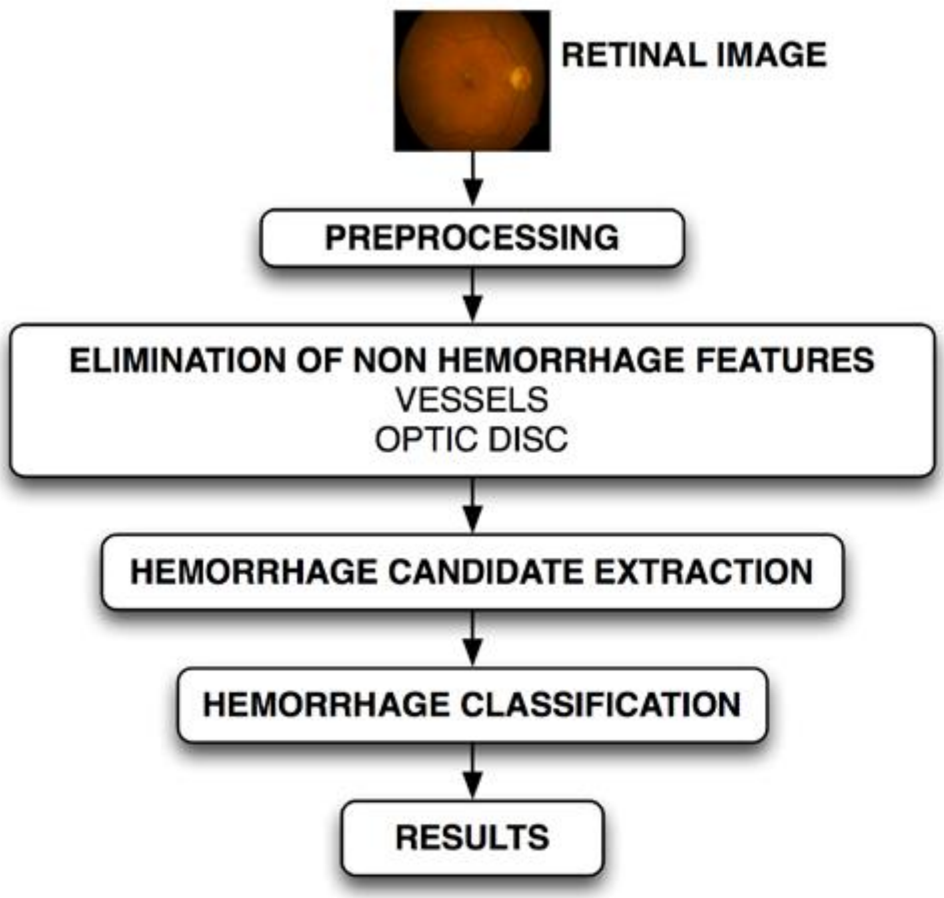

Fig 2. Processes involved in the detection of Hemorrhage

The following subsections review the researches based on their methodologies used for hemorrhage classification.

A. k-NN Classifier

The k-NN classifier has been widely used in applications like image analysis and pattern recognition due to its simplicity. The test instance is classified with the k-nearest training instance based on some distance measure. The Minkowski and Euclidean distance are usually used. Quadratic Discriminant classifier, Linear Discriminant classifier and k-NN classifier is performed on candidate MA objects was proposed in [5]. The k-NN classifier showed the best performance with k=55. k-NN classifier is applied to splat region. The k-NN classifier was applied with 42 features in training and reduced to 7 features using forward feature selection method in testing stage. Different k were tested from the range 21 to 151 for k-NN classifier involved both in feature selection and classification. Parameter k is chosen at 101 because of its performance and accuracy [6]. A set of 20 images are taken from DRIVE database [7] was used for training and then 1200 images from MESSIDOR database [8] are used in testing.

B. Neural Network

Back propagation network is primarily used as a supervised artificial neural network. Application of a neural network is an unsupervised method so training process is needed [9]. Before the training process begins, the selection of architecture plays a major role in determining the accuracy of the classification. The network consists of an input layer, hidden layer and output layer. A weight is used to decide the probability of input data belonging to a particular output. The weights between the layers have to be randomly initialized. The values must be set in the range of [-0.5, 0.5]. Input is presented to the neural network and a corresponding desired or target response is set as the output, an error is calculated from the difference between the desired response and the real system output. The error information acts as a feedback to the system, which makes all adjustments. The weight is adjusted by training the network with a known output. This process is repeated until the desired output is acceptable. Then the network is tested with the data from seen training data and unseen test data. In [10] neural network was applied to candidate MA images with a 500 image training set and 773 image testing set. The training set comprised 147 lesion images and 32 normal images. The images were classified based on presence and absence of lesions. The image was divided into a region of 20x20 pixels or 30x30 pixels before training. The sub-images were classified as 'normal without vessel', 'normal vessel', 'exudates' and 'hemorrhage/ micro aneurysm'

In [11] the learning vector quantization neural network to detect the MA location in retinal angiograms. A small window of 32x32 pixels was used to train the network. Red lesions are detected using multilayer preceptor neural network. The algorithm was tested on 50 images with a set of 29 features that describe the shape and colour of image regions. Multistage training procedure was applied to enhance the performance. The limitation is that the network requires longer training to achieve the desired output.

C. Splat based Classification

In [6] a method was to detect large hemorrhages based on splat feature classification. At first, fundus image was segmented into several splats. Splat is the group of pixels with same colour and spatial location. Each splat can be extracted as a distinct feature e.g., hemorrhages and blood vessels. A classifier was trained to recognize the splats with vessels and then used to extract the vessels from the image, leaving what considered hemorrhage candidates behind. In [12] watershed segmentation procedure was performed (called ''tobogganing'') to generate splats, in which the grayscale version and its gradient magnitude of a image is initially determined, at various scales and then uses their maximum for segmentation. In [13] a set of 43 features were calculated from the pixels in the splat. Features were chosen based on the colour variation in the fundus image. Previously used some features were also present in this set. Then the classifier was trained based on the set of features collected from the images of training set. The classifier is trained by label of the splat (hemorrhage or non hemorrhage), which is derived from the expert created reference standard.

D. Support Vector Machine

Zhang and Chutatape [16] proposed a top-down method for hemorrhage extraction, in which after preprocessing, the hemorrhages were located in the region of interest by using Support Vector Machine (SVM) to calculate the evidence value of every pixel. Combined Two-Dimensional Principal Component Analysis (Combined 2DPCA) was used to extract features which then will be input vector for the SVM classifier. After the location of hemorrhage, features were extracted, the post-processing process can then segment the boundary if the hemorrhages is present in the region of interest. The combination of Combined 2DPCA and SVM was used to achieve higher accuracy of classification. In [15] SVM is used to detect and classify hard exudates effectively. Detection of hard exudates is necessary because they are earliest signs of diabetic retinopathy. Both Support Vector Machine and Discrete Cosine Transform (DCT) analysis use colour information to classify the retinal exudates. The performance of the algorithm was analysed using a database of 1200 retinal images of variable brightness, colour and quality. Color, texture and shape are the top features to look for to differentiate exudates pixels from non-exudates pixels and to extract the significant and relevant features. Features are selected empirically and used as input for SVM clustering. Support Vector Machine (SVM) is applied to classify red lesion areas and non-red lesion areas with 89 retinal images selected randomly from 3 databases STARE, DIARETDBO, and DIARETDBI.

E. Morphological Processing

The most commonly method used for detection of hemorrhages is morphological method, a process used to eliminate the blood vessels. Shivaram et al. [16] used image arithmetic and mathematical morphology methods for detection the hemorrhages and suppressing the blood vessels. result is compared with ophthalmologists' hand-drawn ground truth images pixel by pixel. A morphological reconstruction method [17] for segmentation retina lesion was proposed by Karnowski et al. The segmentation is performed at various scales to find the ground-truth data to separate nuisance blobs from true lesions. They created a "lesion population" feature vector from each image to classify normal or abnormal classes.

TABLE I
ANALYSIS OF CLASSIFIER SELECTION FACTOR

Classifier Parameter sensitive	**Require learning phase**	**High computation cost**	**Require high computer system**	
Neural Network	Yes	Yes	Yes	
Nearest Neighbour	Yes	Yes	Yes	
Splat based Classification	Yes	Yes		
Support Vector Machine	Yes			
Morphological Processing				Yes

III. CONCLUSION

There exists various challenges in the automatic detection of the hemorrhages. It is hard to distinguish hemorrhage from background variations due to its low contrast. Detection of hemorrhage can be confused by other dark areas in the image such as the microaneurysms, blood vessels and fovea. Hemorrhages are in variable size and often they are so small that can be easily confused with the image noise or microaneurysyms and there is no standard database available to classify hemorrhage by shape. The false detection is done in the case when the blood vessels are overlapping or adjacent with hemorrhages. So the effective methodology to detect hemorrhage is needed. This paper analyse all the existing methods to give a complete view about the field. Based on this work, researchers can develop better and more effective algorithms.

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