AN EFFICIENT HEMORRHAGE DETECTION USING SVM CLASSIFIER

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***Abstract*—Diabetic Retinopathy is a medical situation where the retina is injured because liquid leaks from blood vessels into the retina. The occurrence of haemorrhage in the retina is the first indication of diabetic retinopathy. This paper presents novel way for the detection of retinal hemorrhage. Dependable recognition of retinal hemorrhage is vital in the progress of automated screening systems which can be change into system. For the recognition purpose, we first find the location approximately. Under our supervised approach, retinal color pictures are partitioned into nonoverlapping segments covering the complete picture. Each segment, i.e., splat, contains pixels with similar color and spatial position. Set of character is extracted from each splat to demonstrate its character relative to its surroundings. For feature selection, use SVM classifier collection of simpler decisions, thus providing a solution which is often easier. SVM is a classifier which constructs a hyper plane or set of hyperplane in an unlimited dimensional space. The sensitivity and specificity for the detection of abnormal cases was were 80% and 88%, respectively. As we are focused retinal hemorrhage detection, our method has potential to be apply to other object finding tasks.**

KEYWORDS—**RETINAL HEMORRHAGE, DIABETIC RETINOPATHY, SVM CLASSIFIER.**

INTRODUCTION

Diabetic retinopathy is the most frequent diabetic eye disease and important reason of blindness. Automatic evaluation of diabetic retinopathy is vital in timely treatment. Frequently the diabetic patients are suffering from many of the diseases that are found in the retina of the human eye. Microaneurysms, exudates, hemorrhages, drusen, cotton wool spot are the main symptoms of blindness. All the

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above symptoms have to be detected well in progress. A retinal hemorrhage is usually diagnosed by using a fundus camera in order to observe the inside of the eye. A fluorescent dye is frequently injected into the patient's bloodstream in advance so the administering ophthalmologist can have a more detailed examination of the blood vessels in the retina.

The rest of this paper is organized as follows. Section 1 includes the related work. Section 2 includes the proposed model. The proposed architecture is given in Section 3 followed by paper summary and further work in Section 4.

I.RELATED WORK

Our work on evaluation of automated DR detection systems shows that an important cause of false negatives, as high as 50%, is formed by images that contain only large hemorrhages [6]. Large hemorrhages indicate more severe disease, and improved detection of such lesions will lead to elimination of more severe false negatives. Small hemorrhages are regular in shape and many systems have been developed by us and others to detect them [7]–[10]. A review of most recent work on hemorrhage detection can be found in [8]. They primarily fall into three categories: pixel-based approaches, lesion-based approaches, and image-based approaches. Pixel-based approaches focus on the location of hemorrhages on the retina. Lesion-based approaches use morphological operations to define candidate lesions and count them. Image-based approaches are aimed at detecting images or eyes with hemorrhages. However, the size of the lesion is yet another important factor to consider in decision making processes of DR detection systems, which is closely related to the severity of disease that need timely treatment. Large hemorrhages occur infrequently, and their appearance is highly variable, making their shape modeling and automated detection a challenge. Yuji Hatanaka et.al.,(2008) in "Improvement of Automated Detection Method of Hemorrhages in Fundus Images"[9] proposed a new method for preprocessing and false positive elimination. The brightness of the fundus image was changed by the nonlinear curve with brightness values of the hue saturation value (HSV) space. In order to emphasize brown regions, gamma correction was performed on each red, green, and blue-bit image. Then, the hemorrhage candidates were detected. The brown regions indicated hemorrhages and blood vessels and their candidates were detected using density analysis. Removed the large candidates such as blood vessels. Finally, false positives were removed by using a 45-feature analysis. Disadvantage of this system is that it is less accurate. It is a new scheme for automatic detection of hemorrhages using digitized non contrast fundus images. This scheme can be applied to the computer-aided diagnosis (CAD) system for diagnosing eye diseases. Steven C. H. Hoi et.al.,(2006) in "Batch Mode Active Learning and Its

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Application to Medical Image Classification"[1] proposed a framework for "batch mode active learning" that applies the Fisher information matrix to measure the overall in formativeness for a set of unlabeled examples. The key computational challenge is how to identify the subset of unlabeled examples that are overall the most informative to the current classification model. To resolve this challenge, a greedy algorithm is used that is based on the property of sub modular functions. This method is not so effective.

II.PROPOSED MODEL

A. PREPROCESSING:

In preprocessing, first remove background from retinal image. The field of view (FOV) was detected automatically and the images were rescaled to 1026x681 pixels with the FOV approximately 630 pixels in diameter.

B. SPLAT SEGMENTATION

Pixels are part of the same object or structure share similar color, intensity and spatial location, the image is partitioned into nonoverlapping splats of similar intensity covering the entire image. Splat-based representation is an image re-sampling strategy onto an irregular grid. Background regions, with gradual variations in appearance, tend to consist of fewer large splats while foreground regions consist of a larger number of smaller splats. At pixel level, the distributions of hemorrhage pixels and non-hemorrhage pixels are imbalanced, since hemorrhages usually account for a small fraction of the entire image. To create splats which preserve desired boundaries precisely, i.e., boundaries separating hemorrhage from retinal background we perform scale-specific image over segmentation. Due to variability in the appearance of hemorrhage, firstly aggregate gradient magnitude of contrast enhanced dark bright opponency image at a range of scales for localization of contrast boundaries separating blood and retinal background. Then maximum of these gradient over scale of interest is taken in performing watershed segmentation. Assume that scale space representation of image $I(x,y;s)$ with Gaussian kernels Gs at scale of interest

$s \in s1,s2........s_n,$ the gradient magnitude $|\nabla I(x,y;s)|$ is computed from its horizontal and vertical derivatives.

$$|\nabla I(x,y;s)| = \sqrt{\mathrm{I_X}(x,y;s)^2 + \mathrm{I_Y}(x,y;s)^2}$$

$$= \sqrt{[\frac{\partial}{\partial x}(Gs * I(x,y))]^2 + [\frac{\partial}{\partial y}(Gs * I(x,y))]^2}$$

$$= \sqrt{[\frac{\partial G_s}{\partial x} * I(x,y)]^2 + [\frac{\partial G_s}{\partial y} * I(x,y)]^2}$$

symbol * represents convolution and $(\frac{\partial G_s}{\partial x})$, $(\frac{\partial G_s}{\partial y})$ are first order derivative of Gaussian at scale s along horizontal and vertical direction.

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C. FEATURE EXTRACTION

Two categories of features are extracted for splat-based hemorrhage detection as follows: 1) splat features aggregated from pixel- based responses; 2) splat wise features no aggregation is required. Color within each splat is extracted in RGB color space and dark-bright (db), red-green (rg), and blue-yellow (by) opponency images. In aggregation, firstly, the mean and standard deviation (SD) of filtering response within splat p are computed. Secondly, the mean and SD of filtering responses along boundaries of splat p are calculated as additional features of that splat. In addition to splat features aggregated from pixel-based responses, we also extract splat wise features which do not need to be aggregated. Shape features, such as splat area, extent, orientation and solidity, are derived based on individual splat distribution. Texture features are extracted according to the statistics of gray-level co-occurrence matrix (GLCM) and Tamura signatures.Schmid filter bank consisting of 13 rotationally invariant kernels is applied to dark-bright opponency images.Local texture filters include local range filter,local standard deviation filter and local entropy filter which compute the intensity range, standard deviation and entropy of one pixel in a given neighborhood or region.

D. FEATURE SELECTION

Feature selection reduces the dimensionality of feature space by identifying relevant features and ignoring those irrelevant or redundant ones, which is particularly important to a higher separability between classes. There are two major approaches for feature selection: the filter approach and the wrapper approach. The filter approach is fast, enabling their practical use on high dimensional feature spaces. The dataset is partitioned into a training set and a testing set. The goal of feature selection is to exclude those individual features that are not effective or irrelevant in separating hemorrhage /nonhemorrhage splat. Training set is further partitioned into a training subset and testing subset. Splats in training subset are grouped into hemorrhage splat and non hemorrhage splat. The p-values sorted in ascending order are taken as measures of how effective those features are in predicting the correct labels of splats.

E. CLASSIFICATION

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The original SVM algorithm was invented by Vladimir Vapnik and the current standard incarnation (soft margin) was proposed by

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Corinna Cortes and Vladimir Vapnik. The standard SVM takes a set of input data and predicts, for each given input, which of two possible classes the input is a member of, which makes the SVM a non-probabilistic binary linear classifier. Since an SVM is a classifier, then given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other. Intuitively, an SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. More formally, a support vector machine constructs a hyperplane or set of hyperplane in a high or infinite dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

F. PERFORMANCE EVALUVATION

In performance evaluation, the proposed approach is compared with the existing approaches. Some measures often use in the evaluation of medical imaging or diagnostic test for detecting an object such as cancer, hemorrhage etc. A positive observation in an image means that the object was observed in test. A negative observation means that the object was not observed in test. A true condition is the actual truth, while an observation is the outcome of the test. The basic measures are true positive, false positive, false negative and true negative rates or fraction. Performance is analysis on the basis of sensitivity and specificity. Sensitivity is the measure of the proportion of positive which were correctly detected. Specificity is the proportion of negative which were correctly detected.

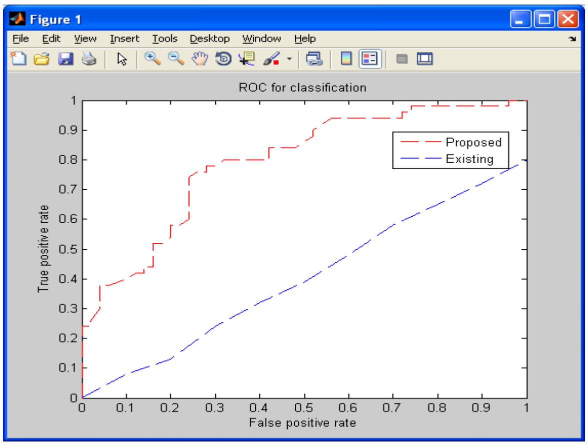

Fig1.Performance Analysis

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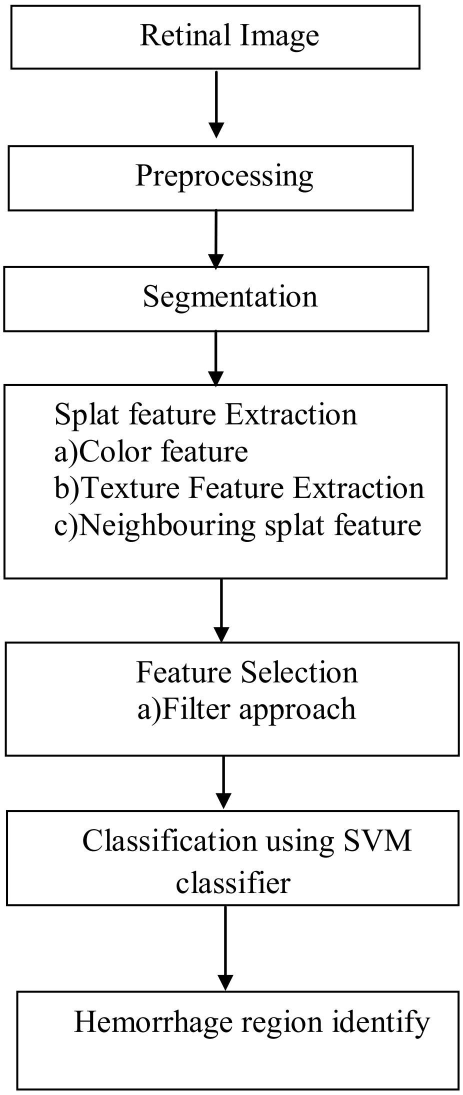
III.PROPOSED ARCHITECTURE



IV.CONCLUSION AND FURTHER WORK

In this project it mainly focuses on splat based feature classification with application to large, irregular retinal hemorrhage detection in fundus photographs. Proposed method is very simple and can detect exudates with very less inspection time. A set of features is extracted from each splat to describe its characteristics relative to its surroundings, employing responses from a variety of filter bank, interactions with neighboring splats, and shape and texture information. An optimal subset of splat features is selected by a filter approach. These splats are taken as samples for supervised classification in a selected feature space. In the previous approach linear data classification only possible. A SVM (Support Vector Machine) classifier is proposed to train with splat-based expert annotations. (SVMs) are a relatively new learning process influenced highly by advances in statistical learning theory and a sufficient increase in computer processing power in recent years. It is an efficient natural way to detect irregular shape abnormalities.

REFERENCES

[1] Abràmoff, J. M. Reinhardt, S. R. Russell, J. C. Folk, V. B. Mahajan,M. Niemeijer, and G. Quellec, “Automated early detection of diabetic retinopathy,” Ophthalmology, no. 6, pp. 1147–1154

[2] http://en.wikipedia.org/wiki/Medical_imaging

[3] G. Li, G. Liqun, P. Zhao-Yu, and W. Kun, “Image segmentation using multiscale gradient toboggan,” in Proc. 2nd IEEE Conf. Ind. Electron.Appl., May 2007, pp. 2206–2209

[4] Jitpakdee, P. Aimmanee, and B. Uyyanonvara, “A survey on hemorrhage detection in Diabetic retinopathy retinal

images," in Proc. 9thInt. Conf. Elect. Eng./Electron.,Comput., Telecommun. Inf. Technol.(ECTI-CON), Bangkok, Thailand, 2012, pp. 14

[5] Meindert niemeijer, Bram van ginneken," Retinopathy online challenge: automatic detection of microaneurysms in digital color fundus photographs" ieee transactions on medical imaging, vol. 29, no. 1, jan 2010

[6] M. Niemeijer, M. D. Abramoff, and B. van Ginneken, "Information fusion for diabetic retinopathy CAD in digital color fundus photographs," IEEE Trans. Med. Imag., no. 5, pp. 775–785, May .2009

[7] M. Niemeijer, B. van Ginneken, J. Staal, M. S. A. Suttorp-Schulten, and M. D. Abràmoff, "Automatic detection of red lesions in digital color fundus photographs," IEEE Trans. Med. Imag., vol. 24, no. 5, pp. 584–592, May 2005.

[8] P. Jitpakdee, P. Aimmanee, and B. Uyyanonvara, "A survey on hemorrhage detection in diabetic retinopathy retinal images," in Proc. 9th Int. Conf. Elect. Eng./Electron., Comput., Telecommun. Inf. Technol. (ECTI-CON), Bangkok, Thailand, 2012, pp. 1–4, vol.

[9] S. C.H.Hoi, R. Jin, J. Zhu, and M. R. Lyu, "Batch mode active learning and its application to medical image classification," in Proc. ICML, 2006, pp. 417–424.

[10] Y.-C. Lin, Y.-P.Tsai, Y.-P.Hung, and Z.-C. Shih, "Comparison between immersion-based and toboggan-based watershed image segmentation,"IEEE Trans. Image Process., no. 3, pp. 632 40, Mar 2008

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