AUTOMATIC DETECTION OF RETINAL HEMORRHAGE BASED ON GABOR WAVELET AND HYBRID KNNSVM ALGORITHM FOR FUNDUS IMAGES

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ABSTRACT

Retinal haemorrhage is the abnormal bleeding of the blood vessels in the retina, the membrane in the back of the eye. In retinal image, automated detection of haemorrhage is a major challenging factor. For automated detection of haemorrhage, a generalized framework is needed to train classifiers with optimal features learned from available dataset. Because of the variability in appearance of these lesions (i.e., haemorrhages), different techniques had been designed to detect each type of these lesions (i.e., haemorrhages) separately in detection system. We need a generalized framework to detect these types of lesions in fundus (i.e., retinal) image. A robust and computationally efficient approach for haemorrhage detection in a fundus retinal image is presented in this paper. Splat feature classification method is proposed with application to retinal haemorrhage detection in fundus images. Automated screening system is very much important to detect a retinal haemorrhages. Based on the supervised approach, fundus images are partitioned into non-overlapping segments covering the entire image. Each splat contains a similar colour and spatial location. A set of features is extracted from each splat using the GLCM & Gabor Wavelet. These features describe a characteristic relative to each pixel in a splat. Supervised classification predicts the likelihood of splats being haemorrhages with the optimal features subset selected in a two-step feature selection process. Preliminary feature selection is done by filter approach followed by a wrapper approach. Hybrid KNNSVM classifier is trained with expert annotation. From the resulting haemorrhages map, a haemorrhage index is assigned. A classifier could evaluate on the publically available dataset. This work will provide a greater AUC in splat level and image level. Our approaches can potential to be applied to other detection tasks.

Keywords — Diabetic retinopathy (DR), fundus images, retinal hemorrhage, KNN, Hybrid KNNSVM, Support Vector Machine, Gabor Wavelet.

I. INTRODUCTION

Automated detection of diabetic retinopathy (DR), as used in screening systems, is important for allowing timely treatment [1], and thereby increasing accessibility to and productivity of eye care providers. Because of its cost-effectiveness and patient friendliness, digital color fundus photography is a prerequisite for automated DR detection [2]. Patients with images that are likely to contain DR are detected and referred for further management by eye care providers.

The most common signs of DR are micro aneurysms, small hemorrhages, exudates, druses, and cotton wool spots. Because of the variability in appearance of these lesions, different techniques have been designed to detect each type of these lesions separately in DR detection systems. Retinal hemorrhages are caused by retinal ischemia and primarily caused by abnormally fragile blood vessels in hypertension, malaria and primarily, pre-proliferative and proliferative DR. Large hemorrhages are asymptomatic except when they are in the center of the macula. Two examples of large retinal hemorrhages are demonstrated. Compared with anatomical structures, such as optic disc, fovea and blood vessels, the shape and appearance of hemorrhages show substantial variability.

Our work on evaluation of automated DR detection systems shows that a noble cause of false negatives, as high as 50%, is formed by images that contain only large hemorrhages. Large hemorrhages indicate more severe disease, and improved detection of such lesions will lead to elimination of more severe false negatives. A review of most recent work on hemorrhage detection can be found in [3]. 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 key 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. Detecting DR lesions is often accomplished by supervised classification [3], which involves training of classifiers using expert labeled target objects at pixel level. Features are extracted from each pixel and soft labels are assigned accordingly, indicating the probability of the pixel being one or part of a target object. Abnormal pixels are then combined into objects.

I. ABOUT RETINAL HEMORRHAGE

A. Definition

Retinal hemorrhage is the abnormal bleeding of the blood vessels in the retina, the membrane in the back of the eye.

B. Diagnosis

Diagnosis of retinopathy is performed by an ophthalmologist, particularly one who specializes in disorders of the retina (retinal specialist). The ophthalmologist may perform an opthalmoscopy, using an instrument called an opthalmoscope to examine the inside of the eye. For a detailed view of the blood vessels of the retina, a fluorescein angiography test might be performed, in which a florescent dye is injected into the patient's bloodstream and photographs record the status of the blood vessels in the retina. Vision tests, patient history, and blood tests might also be ordered by the diagnosing physician.

II. RELATED WORKS

A splat-based feature classification algorithm with application to large, irregular hemorrhage detection in fundus photographs. Neighboring pixels with similar intensity are grouped into non-overlapping splats. A set of features is extracted from each splat to describe its characteristics. These splats are taken as samples for supervised classification in a selected feature space. The algorithm is validated on the publicly available Messidor dataset with an area under the ROC curve (AUC) of 0.96 at the splat level. At the image level, an AUC of 0.87 was achieved.

Splat-based image representation makes it easier for clinicians to annotate the boundaries of target objects, which may lower the cost of acquiring reference standard data for training. It also provides an efficient and natural way to model irregular shaped abnormalities in medical images. Aggregating features within splats improves their robustness and stability, as it is resistant to pixel level noise and intensity bias. Moreover, certain high level texture features are only meaningful when considering regions instead of pixels. Grouping of pixels into splats only depends on the attribute of neighboring pixels instead of the number of pixels contained in each splat. It results in splats on a non-orthogonal grid optimized for image homogeneity.

Sample size is decreased considerably in a splat-based framework, which is an image resampling method. For example, there are 200–300 K pixels within FOV while the average number of splats contained in an image in the Messidor dataset is only approximately 800–900. Decreased sample size leads to substantially less time for classification, which is desirable especially when dealing with large datasets as the one we used in experiments. After the training process, it takes the classifier no more than 15 s to assign hemorrhage/non-hemorrhage splat labels to one image on a computer equipped with a two-core Intel X9650 processor running at 3.00 GHz. On the other hand, experiments with large dataset presented in this study are supposed to reflect more accurately DR screening system performance. Large, irregular hemorrhage detection is a challenging problem because they are rare and irregular in shape with substantial variability in appearance.

To assess performances of an automated system, we conducted image level ROC and FROC analysis, showing that the system can operate at a sensitivity of 93% and specificity of 66%, if the threshold is set to produce an average of 0.2 FPs on a per image basis. Initial evaluations on how the detection of rare large hemorrhages affects overall performance of a DR detection system were encouraging. By integrating the present hemorrhage detector at an appropriate threshold, unweighted performance metrics such as AUC or sensitivity and specificity will not be affected, because the binary reference standard labels only indicate the presence or absence of DR. It will shift the type of false negatives, so that there are fewer false negatives with large hemorrhages, which are never missed by human readers, and more false negatives with retinopathy with only small hemorrhages, even though objectively the severity of diabetic retinopathy is the same for these missed cases.

An image level performance metric is appropriate when the goal is to identify abnormal images. In this scenario, the maximum number of possible FPs or FNs is limited to the number of images that were labeled by experts as normal or abnormal at the image level. However, given splat-based reference standard annotation, experts can provide a binary label but also a quantitative indication of how abnormal those images are. That may lead to insight into the performance of the detector in a more meaningful way. The hemorrhage index, produced as an image-level outcome by taking the total area of abnormal regions in one image, serves as a quantitative indication of the chance of the presence of retinal hemorrhages and more importantly, reflects how abnormal the image is. Images containing many hemorrhages or any large ones should not be missed. It can be compared with a similar measurement provided by human experts, by taking the summation of the annotated binary hemorrhage mask. A positive association between hemorrhage index and its reference standard reveals the ability of the detector in discriminating high-risk images with higher priority. Many of the hemorrhages are connected (continuous) with the retinal vessels. Because many of the false positives in our approach are parts of retinal vessel, an alternative approach would be to mask out all blood vessels using one of the common vessel segmentation methods. However, preliminary studies not presented here show that such an approach, attractive at first consideration, also masked out many of the large hemorrhages we are trying to detect in the first place. Another potential improvement is use of an active learning approach [5], [7]. As we mentioned earlier, one of the problems for supervised classification is its high cost in acquiring labeled data for training. If we design a classifier that can automatically choose examples with the highest classification uncertainty, i.e., at the decision surface boundary, for manual labeling during the learning process, human experts need to label as little data as possible to achieve the same classification confidence. One of the limitations of the current study is that our reference standard was based on that of a single expert, reviewing only part of the dataset. With annotations from additional human experts, it would be possible to compare the variability of experts in interpreting the same set of images in terms of clinical relevance when given the same task description and to get a better definetion of the reference standard. To summarize, we present a splat-based feature classification algorithm with application of hemorrhage detection in fundus photographs. Splat-based feature classification is able to model shapes of various lesions efficiently regardless of their variability in appearance, texture or size. A variety of lesion detection tasks can therefore be generalized into exactly the same framework by training classifiers with optimal features learned from available examples projected onto a sub-feature space which maximizes the inter-class distances while minimizes the intra-class distance. The approach is validated on the Messidor dataset and achieved an area under splat wise ROC curve of 0.96 and an area under image wise ROC curve of 0.87. The hemorrhage detector could be integrated into comprehensive screening systems assisting ophthalmologists in the detection of diabetic retinopathy.

PROPOSED SYSTEM

We proposed that Gabor wavelet and Hybrid KNNSVM classifier will increase the accuracy of output.

A. GABOR WAVELET

Gabor functions are frequently used for feature extraction, especially in texture-based image analysis and more practically in vessel segmentation. Many of image processing tasks can be seen in terms of a wavelet transform. Informally speaking, the image can be seen under the lens with a magnification given by the scale of a wavelet. In doing so, we can only see just the information that is determined by the shape of the used wavelet. The Gabor atoms can also be seen in the words of a wavelet transform. Specifically, Gabor wavelets are created from one particular atom by dilation (and rotation in two-dimensional case). These Gabor wavelets provide a complete image representation. The feature vectors are composed of the pixel's intensity and the Gabor wavelet responses measured at different scales.

Extracting Red, Green, Blue components from input image. The green channel is extracted because; it shows best vessel or background contrast. Red &Blue channels show low contrast and a very noise compared to the green channel. Hence, we select a green channel from a channel separation process. The extracted green channel is inverted before application to wavelet transform so that the vessels appear brighter than the back ground. For feature extraction Gabor wavelet is used. It can detect or calculate mean, standard deviation & variance for every pixels in an input image. And extract feature from that and saved it. Wavelet based image decomposition had done in Gabor wavelet.

B. Hybrid KNNSVM

In this work, supervised classification technique is applied to analyze Fundus Images. Supervised classifycation is a kind of process where known identified samples are classified to reach the targeted result. By this, the data set can be controlled by the analyst. In this process, it is very important to have desired classes and from there appropriate signatures can be formed effectively. The errors of the test image can easily be identified by examining the training set seriously. There are two major activities in this research work such as training process and testing process. In the training process, the Fundus Images have been collected in the form of gray scale format. For this training set, Fundus Images have been taken from publically available dataset. The images are preprocessed to improve the quality of the result. The Gabor wavelet will be calculated from those images to identify texture contents later. The Gabor Wavelet will contain the information about the positions of pixels which have similar grey level values. A co-occurrence matrix will be a two-dimensional array 'P' in which the possible image values will be defined as rows and columns. Then, the texture features will be extracted from the collected stored supervised Fundus Images(training) and those features will be kept in a database for future processes. The Table 2.1 shows the 12 texture features that are extracted from the training set. The Table 2.2 shows the 12 texture features that are extracted from the testing set. However, the dimensionality of the features can considerably be reduced further to increase the speed of the processes. The GLCM features of that image will be computed and the texture features will be extracted in terms of feature vectors. Again, the 12 texture features will be extracted from the given test image. Of these, only the optimized features of the query image will be used for the test such as Entropy, Cluster Prominence etc. The purpose of choosing these 12 features is their high support to the core objective of this research work and sufficient elements to process Fundus Images. Based on these features, the KNN feature space can be formed. Finally, the hybrid algorithm will be applied to classify the given query (test) image. The subsequent steps and other relevant processes are illustrated in the Figure 2.1. As mentioned earlier, initially, the test query MR Image is to be received from the user and its Gabor Wavelet features have to be extracted. Finally, the proposed hybridized KNNSVM algorithm is applied on the given query image. Initially, the KNN will be employed to identify whether the given query image falls in the category of 'Hemorrhage Map1', 'Hemorrhage Map2'' or 'Hemorrhage Map3''. If the result is not concluded, then SVM1 is to be employed to identify the image either as 'Normal' or 'Abnormal'. If 'Normal', the result is concluded, otherwise, SVM2 will be employed to identify whether the stage of hemorrhages. The query image is to be compared with the existing results of training set.

The K-Nearest-Neighbour (KNN) algorithm measures the distance between a test sample and a set of training samples in the features space. Here, the training Fundus Images are supervised classification images and those images have already been labelled. The nearest neighbours for this test sample will be determined using distance measurement functions. Almost, every classification and clustering method needs a distance measure dist (qi, tj) between the query sample and other samples. The aim of the KNN classification is to obtain the nearest-neighbour list. Once the list is received, the query sample is classified based on the majority class of its nearest neighbours.

Hence, if the testing sample is same as the labels of the majority of its K-nearest neighbours, the test sample will be grouped to the category concerned of the classifications. Else, the current process will be switched over to SVM1. If still not concluded the result, the process of classification will be moved to SVM2..

C. Block Diagram

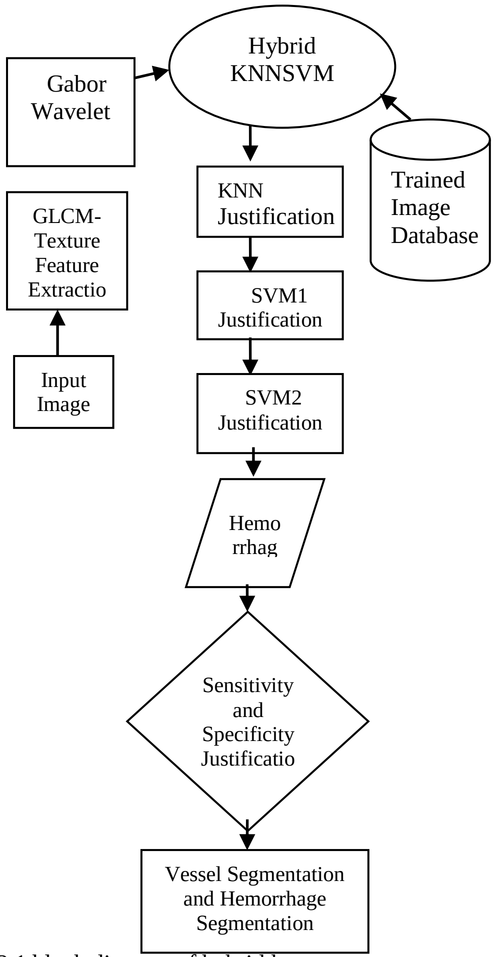

Figure2.1 block diagram of hybrid knn-svm processes

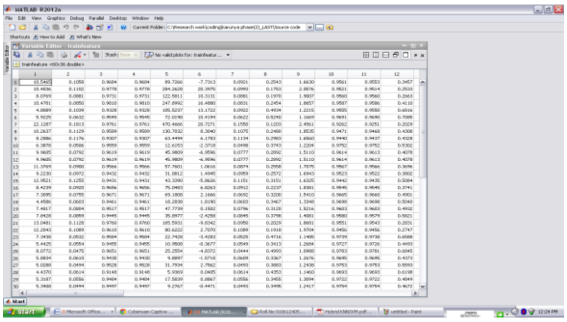

Figure 2.3 Training fundus image database

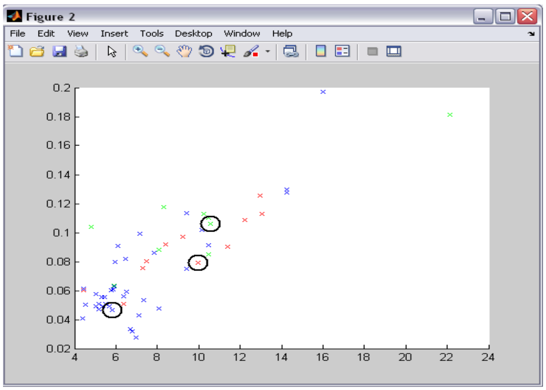

Figure 2.4 Cluster analysis for training database

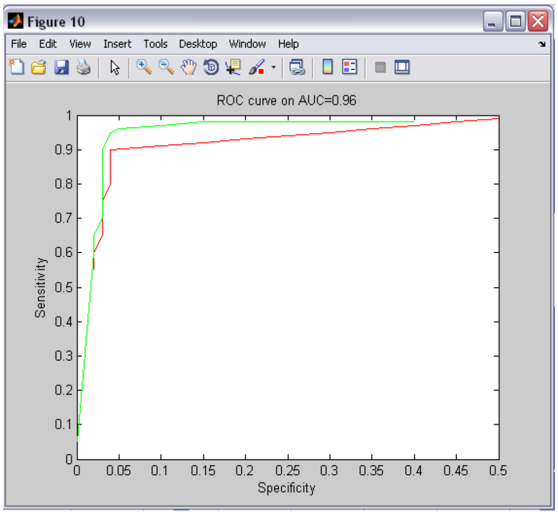

FIGURE 2.5 RESULT

III. EXPERIMENTS AND RESULTS

A set of 60 fundus photographs from publicly available dataset was acquired for testing. Getting an input from a dataset .Each image in the below figure contains a abnormality of the retinal position.

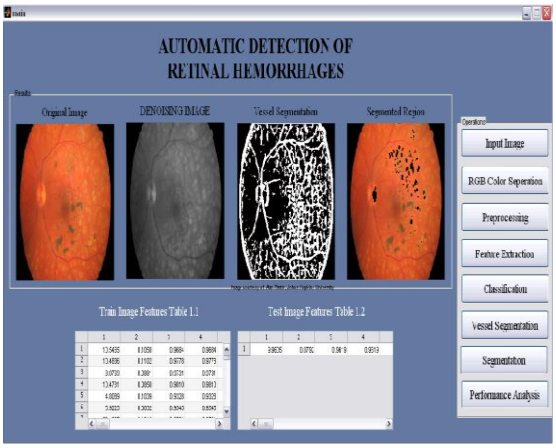

Figure 2.2 Result of classification for the given query image

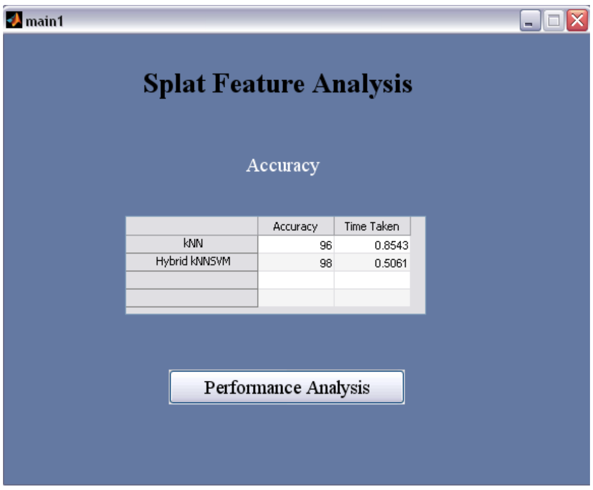

Figure 2.4 Performance analysis

IV. CONCULSION

To summarize, in retinal image, automated detection of hemorrhage is a major challenging factor. For automated detection of hemorrhage, a generalized framework is need to train a classifiers with optimal features learned from available dataset. This work presents a splat-based feature classification algorithm with application of hemorrhage detection in fundus photographs. Splat-based feature classification can detect the hemorrhages regardless of their variability in appearance, texture or size. Splat-based feature classification framework can therefore be generalized to a variety of lesion detection tasks. Our approach is validated on the Messidor dataset and achieved a greater AUC in splat level and image level.

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