



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

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ABSTRACT— Retinal hemorrhage 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 hemorrhage is a major challenging factor. For automated detection of hemorrhage, 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., hemorrhages), different techniques have been designed to detect each type of these lesions (i.e., hemorrhages) 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 hemorrhage detection in a fundus retinal image is presented in this paper. Splat feature classification method is proposed with application to retinal hemorrhage detection in fundus images. Automated screening system is very much important to detect retinal hemorrhages. Based on the supervised approach, fundus images are partitioned into non overlapping segments covering the entire image. Each splat contains a similar color 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 hemorrhages 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 hemorrhageness map, a hemorrhage index is assigned. A classifier could evaluate on the publicly available dataset. This work will provide a greater AUC in splat level and image level. Our approaches can potentially 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 microaneurysms, small hemorrhages, exudates, drusen, and cottonwool 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, preproliferative and proliferative DR. 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. 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]. 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.

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 nonorthogonal 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/nonhemorrhage 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 due to the fact that they are rare and irregular in shape with substantial variability in appearance.

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. we are trying to detect in the first place. Another potential improvement is use of an active learning approach [5], [7]. 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.

III. 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 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 classification 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 in order to improve the quality of the result. The Gabor wavelet will be calculated from those images in order 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.



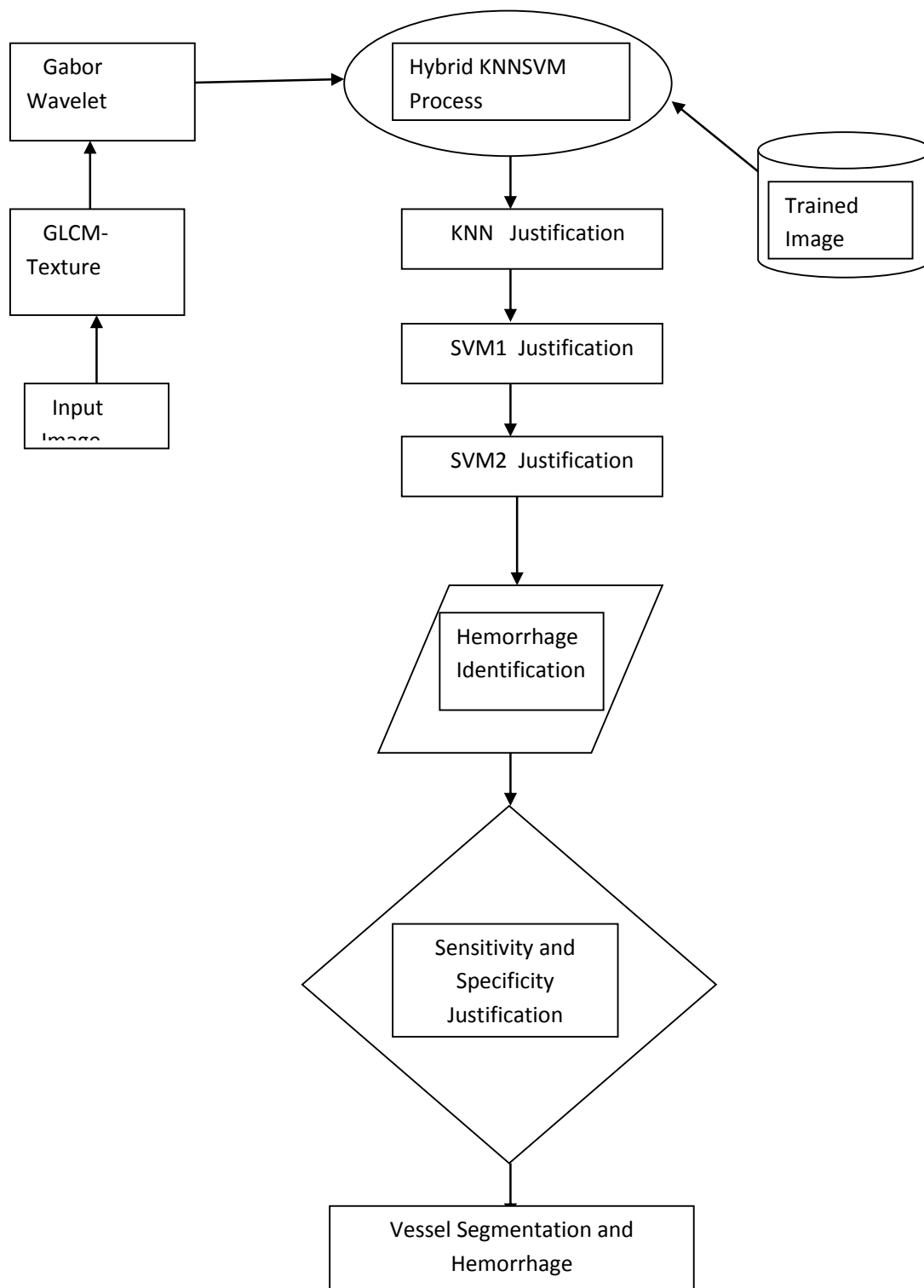
The K-Nearest-Neighbour (KNN) algorithm measures the distance between a test sample and a set of training samples in the features space. Here, the training Fundus Images are supervised classification images and those images have already been labelled. The nearest neighbours for this test sample will be determined using distance measurement functions. Almost, every classification and clustering method needs a distance measure $dist(q_i, t_j)$ 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

A.





IV. 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 an abnormality of the retinal position.

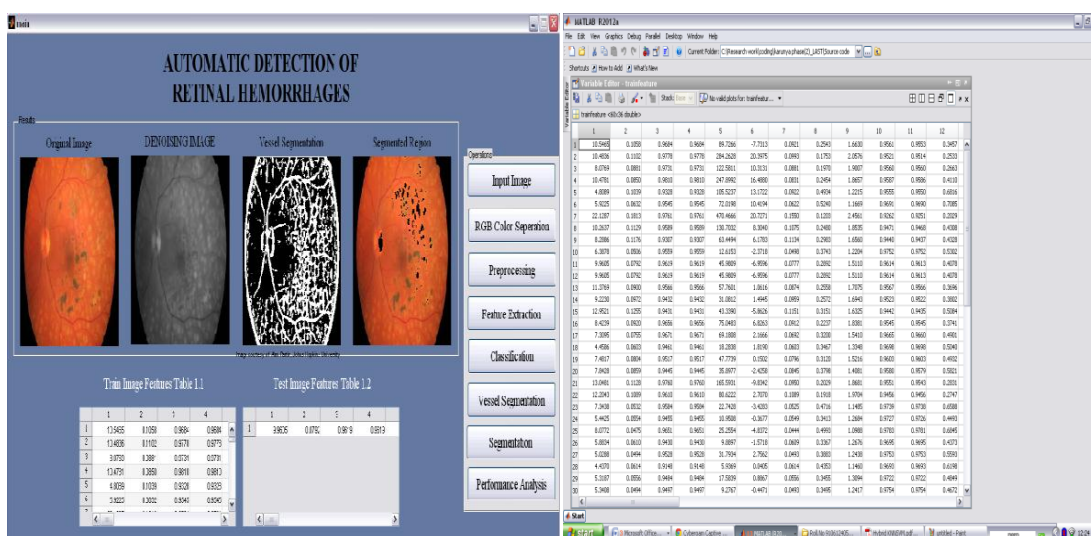


FIGURE 2.2 RESULT OF CLASSIFICATION FOR THE GIVEN QUERY IMAGE

FIGURE 2.3 TRAINING FUNDUS IMAGE DATABASE

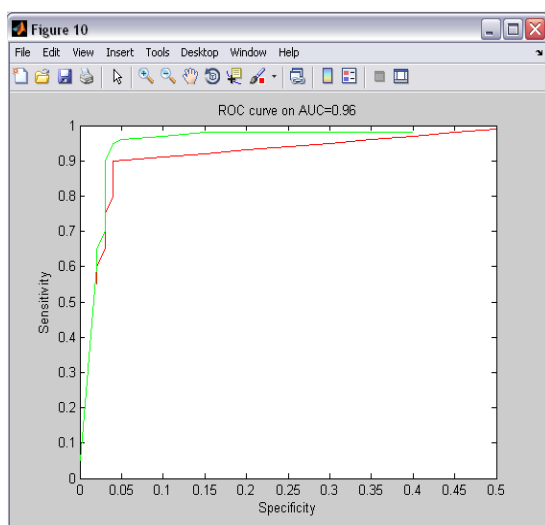


FIGURE 2.5 RESULT

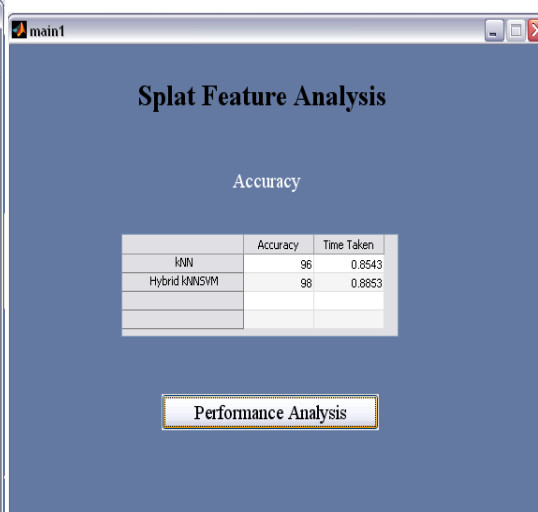


FIGURE 2.4 PERFORMANCE ANALYSIS



V. CONCLUSION

To summarize, in retinal image, automated detection of hemorrhage is a major challenging factor. For automated detection of hemorrhage, a generalized framework is needed to train classifiers with optimal features learned from available datasets. This work presents a splat-based feature classification algorithm with application of hemorrhage detection in fundus photographs. Splat-based feature classification is able to detect 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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