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A Study on the Performance of Splat Based Feature Classification on Fundus Images for the Detection of Hemorrhage and Malarial Diseases

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***Abstract*— The automated detection of diabetic retinopathy and other eye diseases in fundus images of the retina has great promise as a low-cost method. In this paper, an existing splat feature classification method is used to detect the hemorrhage and the malarial disease. Reliable detection of retinal disease is important in the development of automated screening. First, the given test image is segmented by the pixel with similar colour and spatial location covering the entire image. Then the features are extracted from each splat and the relevant features are only taken by the filter approach. A k-NN classifier is used to classify the hemorrhage/ malarial and the non-hemorrhage/ malarial spots. In the hemorrhage and malarial spots a post-processing method with a threshold is used to differentiate the large and the small hemorrhage and malarial spots.**

***Index Terms*—Retina, Splat, Hemorrhage, Malarial, Filter approach.**

I. INTRODUCTION

Diabetic retinopathy is important for allowing timely treatment [1]. 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 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.

Malarial retinopathy (MR) is characterized by retinal hemorrhages of varying sizes and shapes, often showing as Roth spots retinal whitening, papilledema, and vessel discoloration[3].

A method for automated detection of MR hemorrhages has been developed, studied, and validated retinal image analysis algorithms that are capable of detecting retinal lesions such as hemorrhages, exudates, microaneurysms, drusen, and cotton wool spots, as well as measure retinal arterial and venous parameters in retinal colour fundus images, with performance comparable or superior to that of ophthalmologists. A supervised pixel classification and red lesion [4] detection method is proposed based on the analysis of features that include colour, shape, and the response of a Gaussian filter bank.To extract non-hemorrhage and malarial features, non-vessel inhibition operator using Gabor filter has been used to detect vessel feature and a multithresholds scheme based on standard hysteresis thresholding methods is applied to help separate connective elongated vessels from scattered residual edge.

It is expensive to acquire expert labeled reference standards for training and evaluation. Designing such systems requires substantial work by clinicians to define the reference standard, which is expensive and prone to error. Ideally training samples are intended to be both informative to the classification model and diverse so that information provided by individual samples overlaps as little as possible. However, often in a single training image, there can be a huge number of very similar pixel samples. Large hemorrhages /malarial symptoms or diseases occur infrequently [5], have non regular shape and can occur without accompanying other signs of DR, such as micro aneurysms or small hemorrhages and malarial. They will thus be missed by systems designed to detect the regular DR lesions. Because of their low occurrence, sensitivity for detection of large hemorrhages / malarial has negligible effect . In a proposed system a set of feature is extracted from each splat and an optimal subset of splat features is selected by a filter approach which followed by a wrapper approach [6].

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The rest of this paper is organized as follows. Methodologies are described in Section II, Section III gives the experimental results and Section IV concludes the paper.

II. METHODOLOGIES

The architecture of the proposed works is shown in Fig.1.

- Splat segmentation
- Feature extraction
- Feature selection and classification
- Post processing

A. Splat segmentation

Splats are created by over-segmenting images using watershed or toboggan algorithms [7]. Conventional image over segmentation on a regular grid is called "super pixels" [8], [9]. But super pixels are homogeneous in size and shape, resulting in a lattice pattern [10]. A splat-based approach divides images into an irregular grid, i.e., boundaries separating hemorrhages and malarial from retinal background, the scale-specific image over-segmentation is performed in two steps. Due to the variability in the appearance of hemorrhages and malarial, Firstly find gradient magnitudes [11] of the contrast enhanced dark-bright opponency image at a range of scales for localization of contrast boundaries separating blood and retinal background. Next, the maximum of these gradients over Scale-Of-Interest (SOI) is taken in performing watershed segmentation [12]. Time is required to delineate irregular boundaries of hemorrhages and malarial. Any misalignment with true boundaries introduces noise at the training stage This problem may be simplified by splat-based image formulation. For pixel level annotation two types of annotations is allowed by expert: large hemorrhages/malarial and small hemorrhages/malarial. Large hemorrhages/malarial are indicated by a few points along the boundaries (shown as small circles) and then spline fitting is applied to connect those discrete points as enclosed curves. Small hemorrhages/malarial are indicated by a single point.

The edge effect removal is obtained in two ways[13]. One is to fill the region outside FOV with the mean color of the region within FOV. The other possibility is to mirror the FOV outside the FOV. In clear edges still exist as the mean color is not necessary to blend seamlessly with the color on boundaries of FOV[14]. In bright strips are visible on the left and dark strips on the right due to imperfections of illumination or reflection during imaging process.

B. Feature extraction

Features are extracted for splat-based hemorrhage/malarial detection . Color within each splat is extracted in RGB color space and dark-bright (db), red-green (rg), and blue-yellow (by) opponency images [15], which comprise six color components in splat feature space.

The texture features are extracted by considering the gray level co-occurrence matrix [16] and the mean splat responses from difference of Gaussian filter bank [17] is used to show good separability between blood and non blood splats.

C. Splat feature selection and classification

Feature selection reduces the dimensionality of feature space by identifying relevant features and ignoring those irrelevant or redundant ones [18], which are 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. It assesses individual feature separately without considering their interactions. The wrapper approach assesses different combinations of feature subsets tailored to a particular classification algorithm at the cost of longer computation time.

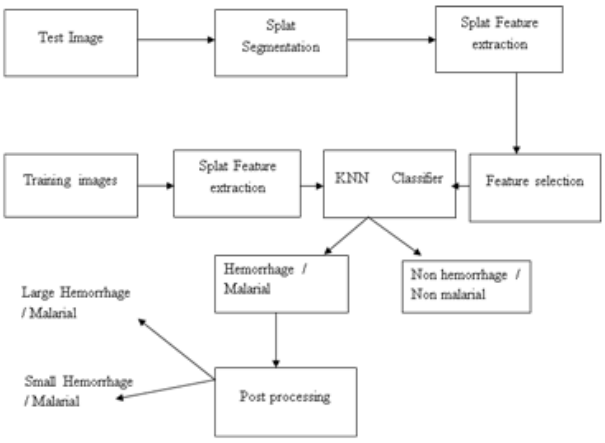

Fig.1. Architecture Design

1) K-Nearest Neighbor (kNN) classification: After feature selection, a trained kNN classifier is set up. The kNN classifier assigns nearest neighbors in the feature space. The distance for finding the nearest neighbors is measured with Euclidean metric in the optimized feature space [19]. Thus, it classifies the hemorrhage/malarial and non hemorrhage/malarial spots.

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D. Post processing

The ultimate goal of splat feature classification is to develop a hemorrhage/malarial detector; firstly low probability responses are suppressed using Eq. (1):

$$h_{(x,y)} = \begin{cases} h_{(x,y)} & \text{if } h_{(x,y)} \geq h_0 \\ 0 & \text{if } h(x,y) < h_0 \end{cases} \quad \ldots\ldots (1)$$

Where h_o is a predefined threshold .With the threshold value the large hemorrhage/malarial and the small hemorrhage and malarial regions are identified from the hemorrhage/malarial spots.

III. Experimental Results

Every methods and algorithms are implemented using MATLAB with the image size of 512x512 and the dataset was created from images available openly on the web. To evaluate the performance of the detection of retinal hemorrhages and malarial techniques several performance metrics are used. The True Positive (TR), True Negative (TN), False Negative (FN), False Positive (FP), Sensitivity (S_e) and Specificity (S_p) are used to analyze the performance.

A. True Positive

The True Positive (TP) is defined as number of correctly detected hemorrhage images to the total number of images. The TP formula is defined in Eq. (2).

$$TP = \frac{Number\ of\ correctly\ Detected\ Hemorrhage\ Images}{Total\ No.of\ Images} \times 100 \ldots\ldots (2)$$

B. True Negative

The True Negative (TN) is defined as number of falsely detected hemorrhage images to the total number of images. The TN formula is defined in Eq. (3).

$$TN = \frac{NumberOfFalselyDetectedHemorrhage\ Images}{TotalNoof\ Images} \times 100 \ldots.. (3)$$

C .False Positive

The False Positive (FP) is defined as number of correctly detected non-hemorrhage images to the total number of images. The FP formula is defined in Eq.(4).

$$FP = \frac{NumberOfCorrectlyDetectedNonHemorrhage\ Images}{TotalNoof\ Images} \times 100 \ldots..... (4)$$

D. False Negative

The False Negative (FN) is defined as number of falsely detected non-hemorrhage images to the total number of images. The FN formula is defined in Eq.(5).

$$FN = \frac{NumberOfFalselyDetectedNonHemorrhage\ Images}{TotalNoof\ Images} \times 100 \ldots.. (5)$$

E. Sensitivity

The Sensitivity (S_e) is defined as the ratio between true positive value and the sum of true positive and false negative value. The S_e formula is defined in Eq. (6).

$$S_e = \frac{TP}{TP + FN} \quad \ldots\ldots (6)$$

F. Specificity

The Specificity (S_p) is defined as the ratio between true negative value and the sum of true negative and false positive value. The S_p formula is defined in Eq. (7).

$$S_p = \frac{TN}{TN + FP} \quad \ldots\ldots (7)$$

The dataset contains images with malarial diseases and hemorrhage. Table 1 shows the performance of the method against hemorrhage.

Table 1
Performance Metrics Value For Hemorrhage Disease

Images	True positive (TP)	True negative (TN)	False positive (FP)	False negative (FN)	Sensitivity (S_e)	Specificity (S_p)
Img1	97.45	2.55	96.54	3.46	0.965712	0.025734
Img2	96.23	3.77	95.32	4.68	0.953622	0.038046
Img3	97.24	2.76	96.42	3.58	0.964491	0.027828
Img4	98.43	1.57	97.34	2.66	0.973687	0.015873
Img5	98.14	1.86	96.41	3.59	0.964711	0.018927

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Table 2 shows the performance against detection of malarial diseases.

Table 2
Performance Metrices Value For Malarial Disease

Images	True positive (TP)	True negative (TN)	False positive (FP)	False negative (FN)	Sensitivity (S_e)	Specificity (S_p)
Img1	91.56	8.44	90.45	9.55	0.905548	0.085347
Img2	89.98	10.02	89.31	10.69	0.891067	0.101191
Img3	91.24	8.76	90.55	9.45	0.906147	0.088208
Img4	90.50	9.5	90.14	9.86	0.900497	0.095477
Img5	92.76	7.24	91.68	8.32	0.912992	0.073697

The results show that (from S_e and S_p) the system could detect hemorrhage with accuracy of 97% and malarial disease with an accuracy of 91%.

IV. Conclusion And Future Enhancement

In this paper the hemorrhage and malarial diseases are detected and classified from the given retinal image. In the hemorrhage and malarial disease detection the location of the hemorrhage and malarial is found out and marked as the white pixels. In the classification phase the hemorrhage and malarial spots is classified and the large and small classes are found from the spots and marked as the separate color. In this paper hemorrhage is obtained with high accuracy rate than the malarial and in the future the malarial accuracy rate will also be increased with other screening techniques.

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