SURF Referral System for Hard Exudates

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***Abstract*—Hard exudates are the leading causes of blindness and blurred vision in individuals suffering from Diabetic Retinopathy. Ophthalmologists become overloaded due to examination of eye fundus images in hard exudates manual detection process. In the presented work a system for detection of hard exudates is proposed. Proposed system is formed through utilization of different mathematical and image processing tools and shows promising results.**

I. Introduction

A rapid increase of diabetes has been observed in the world population in recent years by International medical organizations [1], [2]. According to the statistics published by World Health Organization (WHO) a large population is still undiagnosed and hence untreated [3]. The third world countries are especially in the red zone due to poor or expensive medical facilities. According to the Diabetics' Institute of Pakistan about 12.9 million diabetic patients are present in Pakistan, which are 10% of the entire population [4]. About 3.5 million among them are still undiagnosed [4]. Hard exudates are a common anomaly found in fundus of people having condition of Diabetic Retinopathy. Early detection of artefact is helpful in the diagnosis of the disease. The problem in the diagnosis procedure is that it is a time taking process to examine each fundus image manually by the medical experts. Hence an automated referral system is required to take the load off the medical experts. A study suggests that 36.6% load of the ophthalmologist can be reduced by creating such system [5]. Many researchers have attempted to create such a system. The salient features and results of some works are summarized in Table 1.

In the presented work a referral system is suggested that works by utilizing different mathematical tools like SURF [6], K-means clustering [7], Visual Dictionaries(VD) [8] and a support vector machine (SVM) [9] operating on binary class.

II. PROPOSED TECHNIQUE

As mentioned in section 1, the proposed technique works by blending of different mathematical tools such as SURF, K-means clustering, Visual Dictionaries and support vector machine (SVM). Details of training (section 2.1) and testing (section 2.2) phase has been discussed as under.

A. Training Phase

In training phase SURF is used for detection of different Points of Interest (POIs) in the training images. Fig. 1 shows different POIs detected in in the eye fundus image. The regions around optic dick can confuse the system therefore the POIs detected in the optic disk were ignored.

Fig. 1: (a) Image with artefact

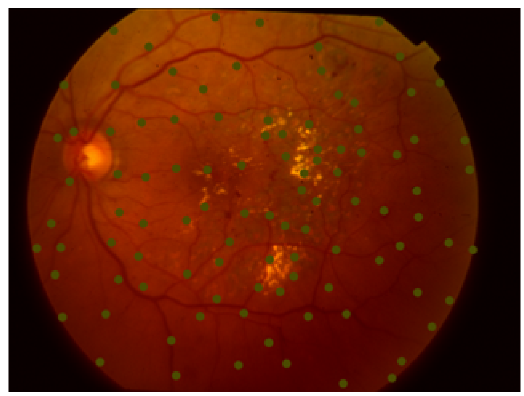

Fig. 1: (b) Image with SURF POIs

It is worth mentioning that the annotations for optic disk and artefact/normal were provided by the medical experts. The features achieved from POIs are dubbed as low level features (LLF). Let d_a and d_n the LLF of the test image I_i for artefact and normal region respectively. Where, $i \in 1, 2, 3, \ldots, m$ and $a \in 1, 2, 3, \ldots, q$, $b \in 1, 2, 3, \ldots, p$. q and p are the total number of LLF obtained from the training image in artefact and normal regions respectively. It should be noted that d_a ,d_n $\in V_y$ i.e. that exist in y-dimensional space.

From these LLF visual dictionary $V = v_1, v_2, \ldots, v_k$ is created by K-means clustering. Here v_k represents a single code word from the visual dictionary V. k can assume any finite number. In the next step the spooling of the LLF is done based on visual dictionary V by mapping each low level feature on V i.e. $f : V^y \to V^K$, $f(d_a) = \mu_a$ and $f(d_n) = \mu_n$. For obtaining $\mu' s$ hard assignment was used [17].

$$\mu_{q,k} = 1 \ _{if} \ q = \arg\min_{\text{k}} \|v_k - d_l\|^2 \ _{else} \ \ q = 0$$

The μ's are now considered as mid-level features and $_{q,k}$ is the q^{th} element of the recently obtained medium level feature (MLF). The MLF still requires spooling step to transform

System Presenters	Images in experiments	Sensitivity	Specificity	Remarks
Sopharak et. al. [10]	60	80%	99.5%	Morphological operations, The intensities of artefact and normal regions vary considerably (Basic Assumption).
Garcia et. al. [11]	117	88%	84%	Features like average and standard deviation are utilized, Operations, were performed on RGB color space different classifiers/ machine learning techniques are employed..
Sopharak et. al. [12]	60	87.3%	99.3%	Works on different Morphological operations, The system needs cautious selection of exudate regions during training, The method needs pre-processing & post-processing steps..
Dupas et. al. [13]	30	92.8%	-	The system works on pixel based classification, Small number of images, is used during experiments authors have provided little details of the results provided.
Welfer et. al. [14]	89	70.5%	98.8%	The system utilizes morphological operations, The techniques are applied on LUV color space, water-shed transform.
Kayal et. al. [15]	219	97.25%	96.85%	Basic image processing techniques are utilized in the system such as , image subtraction median filtering , image addition, dynamic thresholding etc.
Naqvi et. al. [16]	718	92.70%	81.02%	SIFT descriptors, No preprocessing required, large number of images.

TABLE I: Overview of existing methods

it into a high level feature that can be fed into a SVM for training. The high level feature (HLF) is termed as τ and is obtained by sum spooling as:

$$g(\mu_k) = \tau : \forall q, \tau_q = \sum_{k=1}^{N} \mu_{q,k}$$

where, $\tau \in q^k$.

In the next step the high level features are fed into a binary class SVM [9] for training. Table 3 compares the result of our system to some other systems.

B. Testing Phase

In testing phase, procedure described in section II(A) is followed on each testing image to obtain high level features. These high level features are then fed into an already trained binary class SVM to determine their class i.e. if the training image needs referral or not.

III. USED DATASETS AND EXPERIMENTS

A. Choice of Databases

Three datasets are used to accomplish the experiments. DR1 [18] and DR2 are databases produced by Federal University of Sao Paulo. DR1 holds 234 hard exudates images of resolution 640×480 of our interest. DR2 contains 79 images of hard exudates of resolution 867×575 of our use. Diaret db1 [19] is the third database used in our work. The medical experts recognized 46 images of resolution 1500×1152 as containing hard exudates.

B. Experiments

In the experiments the images of the three datasets comprising of hard exudates were mixed to give the system more challenging situation. The purpose to mixing was to judge the performance of the system in a more practical situation when the images originate from diverse sources. Therefore 359 images with hard exudates and 359 normal images were chosen. In total 718 images were used from which only 80 were used for training. All other images were used for testing. The merging of images from diverse datasets may create biasing effects therefore the experiments were executed three times using Random Sub-sampling [20]. Random Sub-sampling itself provides a more challenging scenario to the system as compared to cross validation methods. The random sets in random sub-sampling were chosen by the computer and were termed as RS 1, RS 2 and RS 3. Moreover the tests were executed on four sizes of the visual dictionary termed as VD 50, VD 150, VD 250 and VD 350. Note that VD 50 means that 50 code words are taken from artefact regions and 50 code words are taken from normal regions of the images. Identical convention is shadowed in other VDs.

IV. RESULTS AND DISCUSSION

Table 2 displays the results of the experiments in terms of Sensitivity and Specificity. The Area under the curve and Accuracy has also been calculated. The formulae of sensitivity and specificity are shown below [21]:

$$sensitivity = \frac{TP}{TP + FN} \quad , \quad specificity = \frac{TN}{FP + TN}$$

Where, TP=True Positives, TN=True Negatives, FP=False Negatives, FP=False Positives.

VD Size	RS	Sensitivity	Specificity	ACC	AUC	SD	Avg. AUC
VD 50	RS 1	76.83%	89.96%	83.40%	0.8715	0.043	0.8321
	RS 2	74.90%	85.71%	80.31%	0.8387		
	RS 3	66.41%	86.49%	76.45%	0.7861		
VD 150	RS 1	82.24%	94.21%	88.23%	0.9025	0.0107	0.8926
	RS 2	86.16%	85.71%	85.94%	0.8812		
	RS 3	83.78%	92.66%	88.22%	0.8942		
VD 250	RS 1	93.82%	83.01%	88.42%	0.9010	0.027	0.8908
	RS 2	83.40%	95.75%	89.58%	0.9113		
	RS 3	85.71%	83.01%	84.36%	0.8601		
VD 350	RS 1	82.24%	89.19%	85.72%	0.8863	0.036	0.8942
	RS 2	89.96%	93.82%	91.89%	0.9343		
	RS 3	78.76%	88.80%	83.78%	0.8621		

TABLE II: Results acquired on various VDs for RS 1, RS 2 and RS 3 blend of image databases through SVM

We can see from Table 2 that maximum AUC of 0.9342 is obtained on RS 2 when the VD is kept on VD 350.The highest accuracy of 91.89% is also recorded on the same parameters. The maximum Average AUC within the VD is 0.8942 on VD 350. The minimum standard deviation (SD) of 0.0107 is observed on VD 150. Fig. 2(a-c) displays the results of all three RS on VD 50, VD 150, VD 250 and VD 350.

Fig. 3(a-d) shows another view of the obtained result on RS 1, RS 2 and RS 3 by keeping the VD constant.

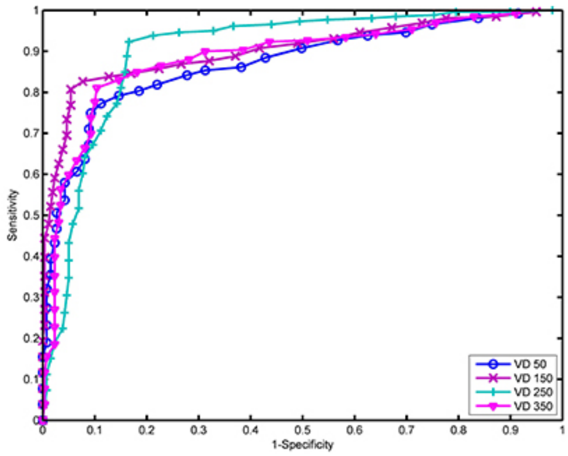

Fig. 2: (a) Results of different VDs on RS 1

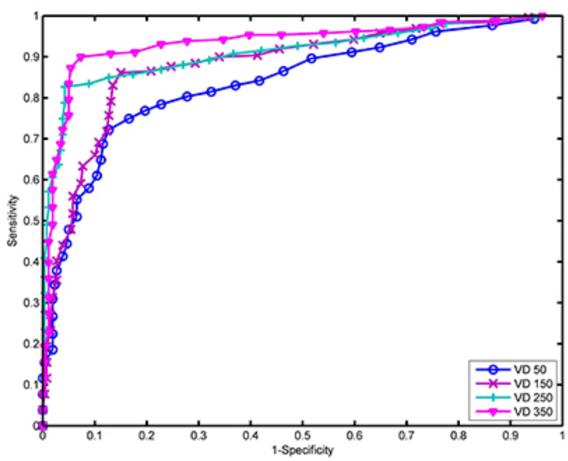

Fig. 2: (b) Results of different VDs on RS 2

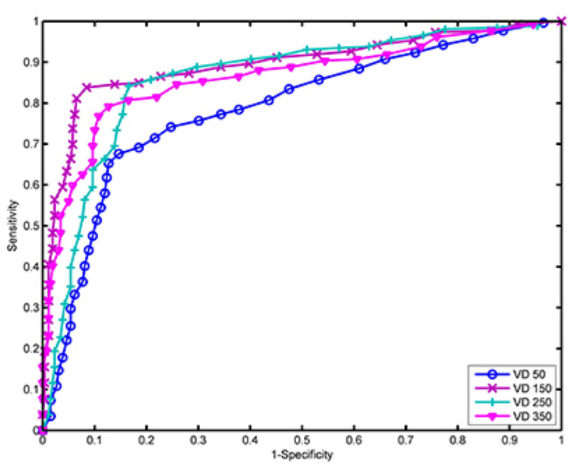

Fig. 2: (c) Results of different VDs on RS 3

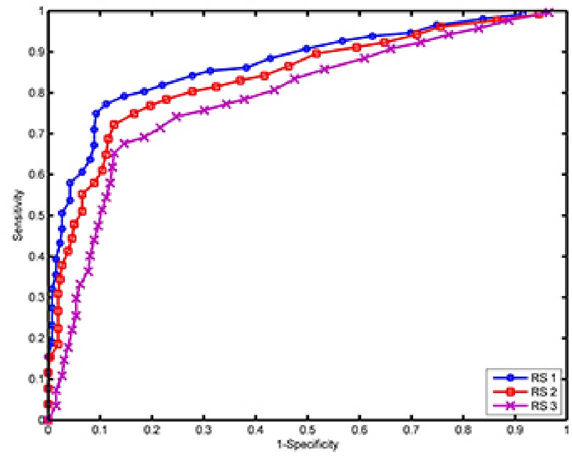

Fig. 3: (a) Results of different RS within VD 50

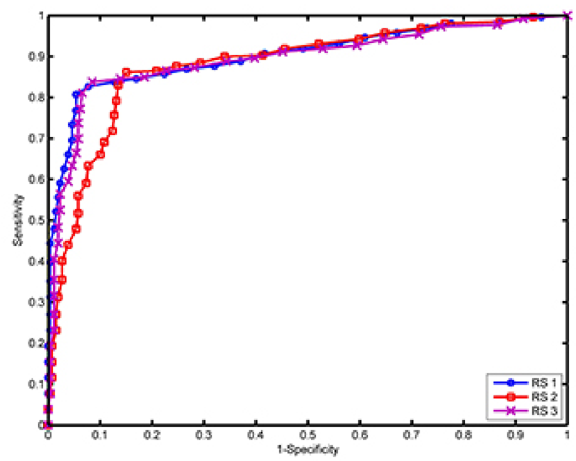

Fig. 3: (b) Results of different RS within VD 150

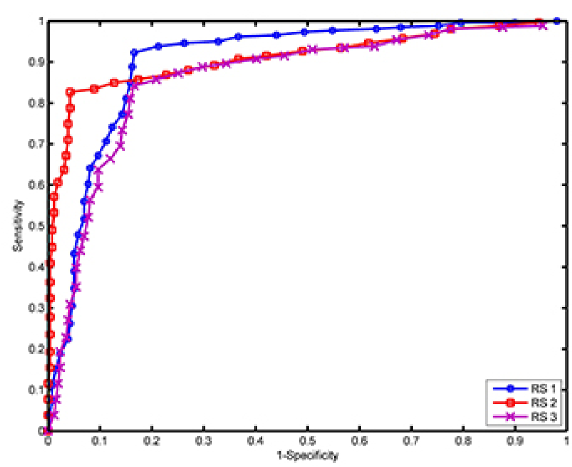

Fig. 3: (c) Results of different RS within VD 250

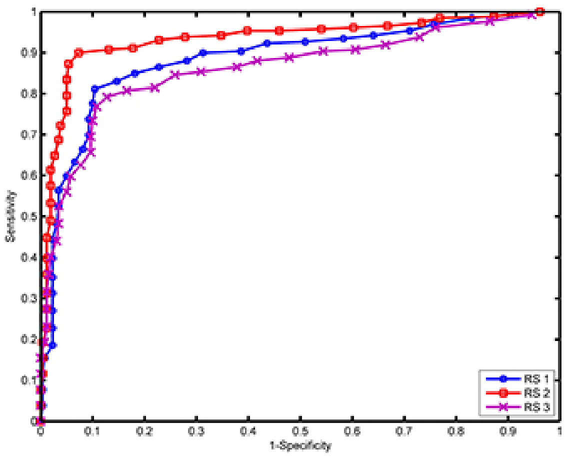

Fig. 3: (d) Results of different RS within VD 350

Table 3 compares the result of our system to some other systems.

System Presenters	Sensitivity	Specificity	Accuracy(ACC) (%)
Diri et. al. [22]	72.82%	-	-
Marin et. al. [23]	-	-	72.82%
Lam et. al. [24]	-	-	94.74%
Naqvi et. al. [16]	92.70%	81.02%	87.23%
Presented work	93.82% (max)	95.75% (max)	91.89% (max)

TABLE III: Comparison of existing methods

V. Conclusion

The presented work elucidates a referral system for hard exudates in the digital eye fundus images. Although a very challenging scenario was given to the system through the use of random sub-sampling instead of cross validation, the system still shows better/comparable results. In the future more adjustments will be made in the system by combining different mathematical tools and testing them on better scenarios.

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