Hard Exudates Referral with Artificial Neural Network

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Abstract—**Medical Imaging systems have already proved their worth in providing cheap medical facilities to the population. Over the years the medical experts are becoming more and more concerned about the increased rate of patients facing the medical condition of diabetic retinopathy. The medical experts are becoming over loaded and a need for an automated system is established. The work presented in the paper discusses a system for referral of hard exudates. The system has been formed by combing various methods like SIFT, K-means clustering, visual dictionaries and artificial neural networks. The system displays promising results.**

Keywords—Artificial Neural Network, Diabetic Retinopathy, SIFT, Hard Exudates.

I. Introduction

THE rate of patients suffering from diabetes is increasing day by day. World Health Organization (WHO) has estimated that currently there are 347 million patients affected from diabetes in the world [1]. About 80% of the population lives in under developed country and is still untreated or undiagnosed [1]. Most of the diagnosis procedures are expensive or out of reach of the patients. Hard exudate is a common artifact in eye fundus images of the patients facing the medical state of diabetes [2]. They are also one of the earliest signs of the arising complications in the patients. Therefore diagnosis of hard exudates may lead us to the early identification of the patients suffering from diabetes. Through the use of digital eye fundus image the procedure becomes patient friendly, cost effective and noninvasive. Due to the mentioned qualities, the method seems fit for the profile of third world and under developed countries. However it requires extensive time for the medical expert to diagnose the patient with medical problems, through use of this method. The medical experts have become over loaded. A referral system may help the medical expert by eliminating the images of the patients who do not have hard exudates in their eye fundus. A study suggests that 36.6% work of the medical experts may be removed through these systems [3].

In the presented work a referral system is suggested that engages different techniques like SIFT [4], K-means clustering [5], Visual word dictionaries [6-7] and artificial neural networks [8].

II. Literature review

An important work regarding the problem was done by Sopharak et al. [9]. It used various morphological operations for the purpose. The work assumed that the intensities of the artifact regions were separable from the normal regions. The system attained 80% sensitivity and 99.5% specificity. Garcia et al. [10] used basic features of image such as average and standard deviation. The authors used RGB color space in the technique. Various classifiers/machine learning techniques were used. The system attained 88% sensitivity and 84% specificity. Sopharak et al. [11] utilized different morphological operations after careful selection of exudate regions in training. This system required careful pre-processing and post-processing. The system attained 87.3% sensitivity and 99.3% specificity. Welfer et al. [12] also used morphological operations but in LUV color space. The watershed transform was also utilized and attained 70.5% sensitivity and 98.8% specificity. Kayal et al. [13] made use of basic image processing techniques like median filter, image subtraction, image addition and dynamic thresholding. Their system attained 97.25% sensitivity and 96.85% specificity.

III. Proposed Technique

The suggested system operates by merging different mathematical tools like SIFT, K-means clustering, visual word dictionaries and artificial neural networks. In the first step the system undergoes a training phase. During training phase the SIFT descriptors are detected in the training images. These descriptors act as level-1 features. Level-1 features are in y-dimensional space. It must be noted that these level-1 features need two further processing steps to reach level-3 features to make them ready for feeding into a neural network. The level-1 features are separated by the system into artifact and normal region pools, based upon the annotations provided by the medical experts. From leval-1 features a visual word dictionary is also prepared using k-means clustering, in such a way that the visual dictionary contains half artifact and half normal region code words. To get the level-2 features the process of quantization is done. In the quantization process the level-1 features are mapped onto the visual dictionary (f: $v^y \rightarrow v^k$) by using the hard assignment [14]. The level-3 features are obtained by spooling process through formula.

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

Where $\tau \in \mathbb{R}^k$ is a single level-3 feature. $\mu_{q,k}$ is the qth element of level-2 feature. Level-3 features are fed into an artificial neural network for training. In the testing phase almost same procedure is followed. Level-1 features are obtained through the use of SIFT. However level-2 features are obtained by using the same visual word dictionary prepared in training phase. To acquire level-3 features, the procedure of training phase is followed. The level-3 features of testing phase are fed into the artificial neural network for accessing the validity of the system. The method of random subsampling [15] was used in the training and testing phases.

IV. DATASET

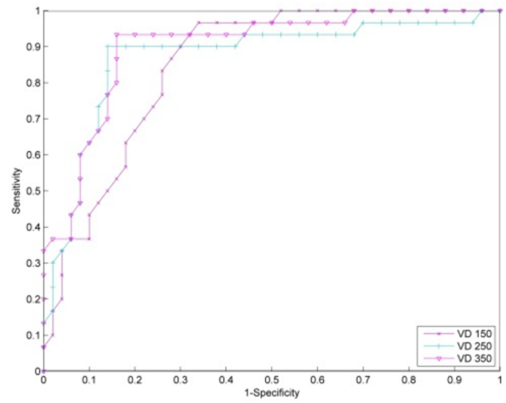
The dataset used in the experiment is STARE [16] digital eye fundus image dataset. The images are compiled by Shiley Eye Center of University of California. In the dataset total numbers of 78 images were found containing hard exudates. The resolution of the images is 700x605 pixels.

Table 1. Obtained Results

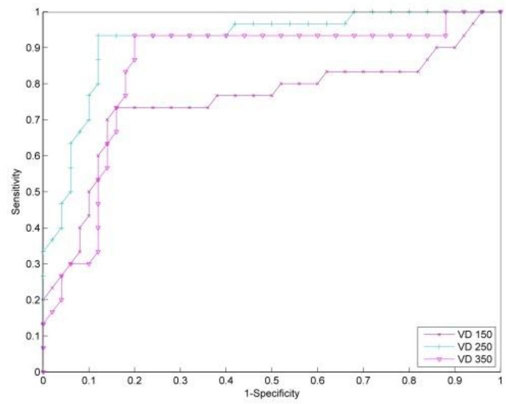
Size of Visual Dictionary	Random Set	Sensitivity (%)	Specificity (%)	Area under the Curve (AUC)	Accuracy	Average AUC
VD 150	RS 1	93.33	70.00	0.8527	81.67	79.78
	RS 2	70.00	86.00	0.7520	78.00	
	RS 3	73.33	86.00	0.7953	79.67	
VD 250	RS 1	90.00	86.00	0.8707	88.00	89.45
	RS 2	93.33	88.00	0.9187	90.67	
	RS 3	93.33	86.00	0.9127	89.67	
VD 350	RS 1	93.33	84.00	0.9000	88.67	84.78
	RS 2	93.33	80.00	0.8433	86.67	
	RS 3	80.00	78.00	0.7507	79.00	

V. RESULTS

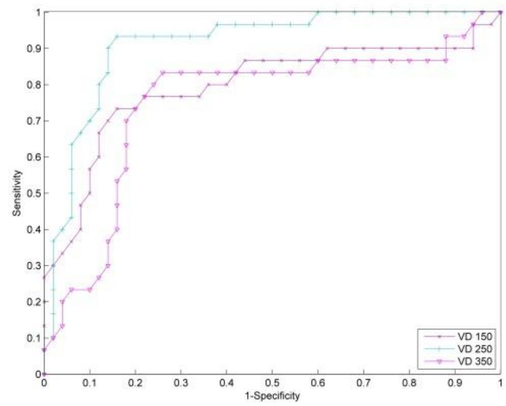
In the experiment 40 images comprising of hard exudates and 40 normal images were utilized while training where as rest of the images was utilized in testing phase. The experiments were accomplished of three sizes of the visual word dictionaries i.e. VD 150, VD 250 and VD 350. While making VD 150 a total number of 300 code words were selected from which 150 were code words of artifact regions and 150 code words of normal regions. Same routine was followed in other VDs. In random subsampling three random sets were selected by the computer. The random sets were named as RS 1, RS 2 and RS 3. The results obtained are shown in Table 1 showing sensitivity, specificity, area under the curve(AUC), accuracy on various sizes of VDs and RS. Table 1 also displays the average AUC within the specified VD.It is clear from Table 1 that the maximum sensitivity is obtained VD-RS pairs 250-2, 250-3, 350-1 and 350-2. The maximum specificity is observed at VD-RS pair 250-2. The maximum area under the curve is noticed at VD-RS pair 250-2. The maximum average AUC inside VD has be seen on VD 250. The performance of RS 1, RS 2 and RS 3 on different VDs are shown graphically in Fig. 1(a-c). Another graphical view of the performance of the system is shown in Fig. 2(a-c) when the size of VD is kept constant. The comparison of the system which used STARE data set is made in Table 2.



1(a)

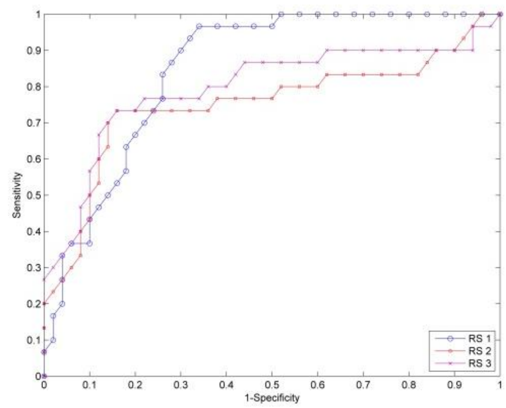


1(b)

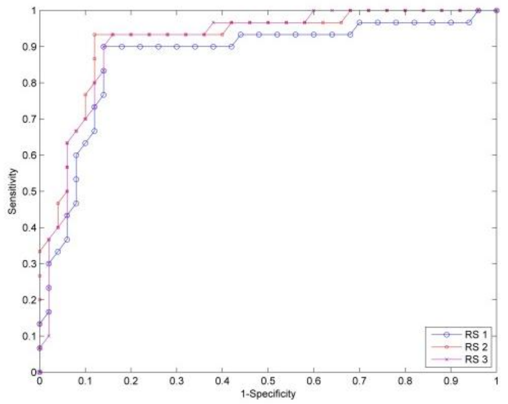


1(c)

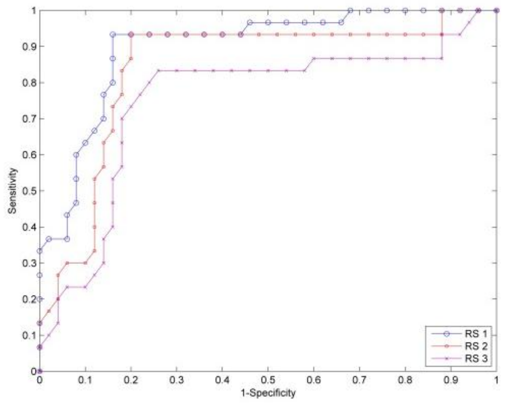
Fig. 1. Results of different VDs on (a) RS 1 (b) RS 2 (c) RS 3



2(a)



2(b)



2(c)

Fig. 2. Results of different RS within (a) VD 150 (b) VD 250 (c) VD 350

VI. Conclusion

In the paper a system for referral hard exudates has been suggested. The system is formed through the use of various techniques like SIFT, k-means clustering, visual word dictionaries and artificial neural network. The performance of the system is found to be better / comparable to the existing systems. The maximum sensitivity attained by the system is 93.33% whereas the maximum specificity attained is 88.00%. The maximum area under the curve is found to be 90.67%.

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