ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

Classification of Hard Exudates in Fundus Images using Support Vector Machine Classifier.

S Antelin Vijila[1]*, and RS Rajesh[2].

Department of Computer Science and Engineering, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India,

ABSTRACT

Diabetic retinopathy (DR) is one of the potential complications of diabetes that may cause blindness in people worldwide. The purpose of computer-aided detection or diagnosis (CAD) technology has to serve as a second reader for the radiologists. This paper presents an algorithm based on Support Vector Machine for the computer-assisted detection of exudates in fundus images of human retina for the diagnosis of diabetic retinopathy. The disease is diagnosed by the presence of exudates in the macular region. The selected feature vectors are then classified using a Support Vector Machine classifier. The algorithm was implemented using a large image dataset consisting of 300 manually labeled retinal images, and could identify affected retinal images with 95.0% sensitivity and specificity of 92.3%.

Keywords: Diabetic retinopathy, fundus image, support vector machines, retinal exudates, Computer aided detection.

Corresponding author

INTRODUCTION

Retinal images of humans play an important role in the detection and diagnosis of many eye diseases for ophthalmologists. Some of the diseases are glaucoma, Diabetic retinopathy and macular degeneration. Diabetic Retinopathy is a severe and widely spread eye disease which can be regarded as manifestation of diabetes on retina. The primary effect of DR is that it can cause vascular damage on the retina before the patient develops more severe symptoms. The damage on the retina is not uniformly distributed, which means the relation of pupil response to light stimulus on the center of the retina and on the peripheral of the retina will be different for a patient with DR and a healthy person. Images of the ocular fundus, i.e., retinal images, can assist in the diagnosis and treatment of retinal, ophthalmic, and even systemic diseases, such as diabetes, hypertension, and arteriosclerosis. Automatic detection of lesions in retinal images can assist in early diagnosis and screening of Diabetic Retinopathy. Exudates are the primary sign of Diabetic Retinopathy. So detection of exudates is the fundamental requirement to diagnose the progress of Diabetic Retinopathy.

Numerous algorithms have been proposed to detect early signs of DR from Colour Fundus Images. The first such method was presented by Oien et al. [11]. In later methods, a rule-based classification was added to the processing pipeline [6, 8, 12, 13].

In the lesion-based criterion, each single exudate lesion is regarded as an individual connected region, where this region can comprise one or more pixels. Each abnormal retinal image can be segmented into a number of exudate regions. By considering a set of retinal images and applying an appropriate segmentation technique, a dataset of exudate regions will be created.

Exudates detection and identification was investigated by Phillips et al. [2, 3]. In image-based diagnostic assessment way, each image is examined and a decision is made to illustrate whether the image has some evidence of DR, purely based on the absence or presence of exudates anywhere in the image.

Detecting retinal exudates in a large number of images that are generated by screening programmes [1] and need to be repeated at least annually is very expensive in professional time and open to human error. With this motivation in mind, we have developed an intelligent system using Support Vector Machine classifier to automate the preliminary analysis and diagnosis of DR disease. This system combines computational intelligence and pattern recognition with machine learning techniques to analyze diabetic retinal images. Through this system, the abnormal retinal images are automatically discriminated from normal images, and an accurate assessment of retinopathy severity is obtained at pixel level.

Computational intelligence has emerged as a rapidly growing field in recent years. Its various techniques, e.g., Neural Networks, fuzzy systems, evolutionary computing and machine learning have been recognized as a collection of powerful tools for intelligent information processing, decision making, and knowledge management in applications such as medical diagnosis. This could be due to the potential of these systems to deal in a suitable way with imprecision, uncertainty, and partial truth. In this paper the classification of hard exudates using support vector machine is done for the fundus images.

MATERIALS AND METHODS

Image Acquisition

A large dataset was constructed with manually labeled images for both training and testing of our method. This dataset consists of 300 images taken from a screening program for DR. The images were acquired using a Cannon nonmydriatic CR6-45NM camera. Each image was captured using 24 bit per pixel at a resolution of 760×570 pixels. Of the 300 images in the dataset, 150 are of patients with no pathologies (normal) and the rest of the images are abnormal (contain pathologies such as exudates, cotton wool spots, microaneurysms, and hemorrhages). Examples of such images are shown in Fig. 1.

ISSN: 0975-8585

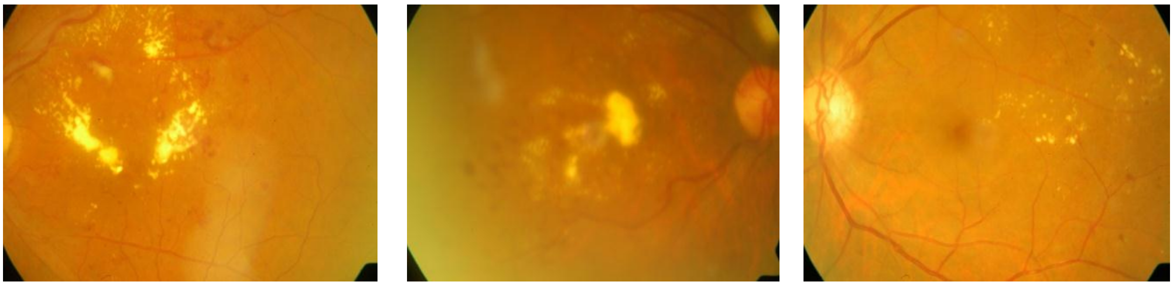

Figure 1: Examples of DR images.

Preprocessing

Typically, there is wide variation in the color of fundus from different patients that is strongly correlated to the person's genetic and their iris color. Therefore, we are using two preprocessing steps before commencing the detection of exudates. The first step is normalizing the color of the retinal images across the dataset. We selected a retinal image as a reference [Fig. 2(a)], and then applied histogram equalization to modify the values of each image in the database [for example, Fig. 2(b)] such that its frequency histogram matched the reference image distribution.

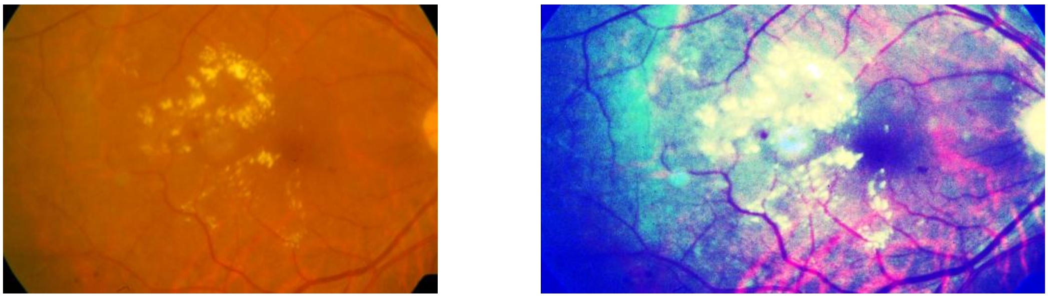

Figure 2: (a) Fundus Image, (b) Histogram equalized Image.

The histogram specification technique was independently applied to each individual RGB channel to match the shapes of three specific histograms of the reference image. Here, the reference histograms were taken from an image, which represents a frequent retinal pigmentation color among our image dataset. This image was chosen in agreement with the expert ophthalmologist.

Feature Extraction

After pre-processing the image it need to be identified in terms of exudates and non-exudates. This is attempted, in a bottom-up approach, by extracting a set of features for each region and classifying the regions based on the generated feature vectors.

The normalized red, green and blue components of the preprocessed image were extracted as features for the classification phase. The features extraction process was done as in reference[9]. The colour component makes an accurate classification in the hard exudates separation process and gives a good measure.

Classification using Support Vector Machine Classifier

SVM is a constructive learning procedure rooted in statistical learning theory [10, 14]. It is based on the principle of structural risk minimization that is used to minimize the bound on the generalization error (i.e., error made by the learning machine on data unseen during training) rather than minimizing the mean square error over the data set. As a result, this leads to good generalization and an SVM tends to perform well when applied to data outside the training set.

SVM schemes use a mapping into a larger space so that cross products may be computed easily in terms of the variables in the original space making the computational load reasonable. The cross products in the larger space are defined in terms of a kernel function $K(x, y)$ which can be selected to suit the problem. The hyperplanes in the large space are defined as the set of points whose cross product with a vector in that space is constant. The vectors defining the hyperplanes can be chosen to be linear combinations with parameters α_i of images of feature vectors which occur in the data base. With this choice of a hyperplane that points x in the feature space which are mapped into the hyperplane are defined by the relation,

$$\sum_{i=1}^{N_s} \alpha_i K(x, s_i) = b \qquad (1)$$

Where $s_i, i = 1,2,\ldots\ldots, N_s$, is the subset of training samples $\{x_i, i = 1,2,\ldots\ldots, N\}$ are the support vectors and b is a constant value. By introducing the kernel, SVMs gain flexibility and SVMs can be robust, even when the training sample has some bias. The support vectors in the Fig 3 are elements of the training set that lie exactly on or inside the decision boundaries of the classifier. The classifier uses these borderline examples to define its decision boundary between the two classes (i.e Exudates 'present' or 'absent').

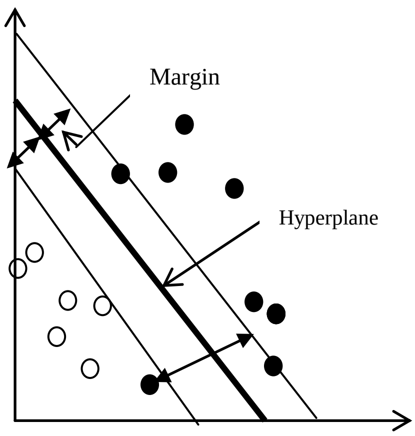

Figure 3: Support Vector Machine with a hyperplane

EXPERIMENTAL ANALYSIS AND RESULTS

To investigate the effectiveness of the proposed method, an image dataset of 300 labeled retinal images including 150 normal and 150 abnormal images is considered. In most cases, medical images are based on carrying less information than color images. Medical images are usually low resolution and high noise images. Moreover, color and intensity are not as important in medical images as in photographs; texture analysis becomes crucial in medical image. Texture also refers to visual patterns which have properties of homogeneity and cannot result from the presence of only a single color or intensity [4]. Texture perception plays an important role in the human visual system of recognition and interpretation. The texture features were captured for each pixel and were extracted from the DR and normal images. For the purpose of SVM training a total of 2050 patterns were taken which has both normal and abnormal pixels.

The designed SVM classifier is a two class classifier that organizes all training sets into two classes, namely, 'Exudates present' and 'Exudates absent'. The kernel function plays a central role of implicitly mapping the input vector into high dimensional feature space, in which better separability is achieved. There are two common kernel functions for nonlinear feature mapping 1. Gaussian function 2. Polynomial function. Many classification problems are always separable in feature space and are able to obtain better accuracy by using the Gaussian kernel function than the linear and polynomial kernel functions [15], [16].the Gaussian radial basis function (RBF) kernel used has the form,

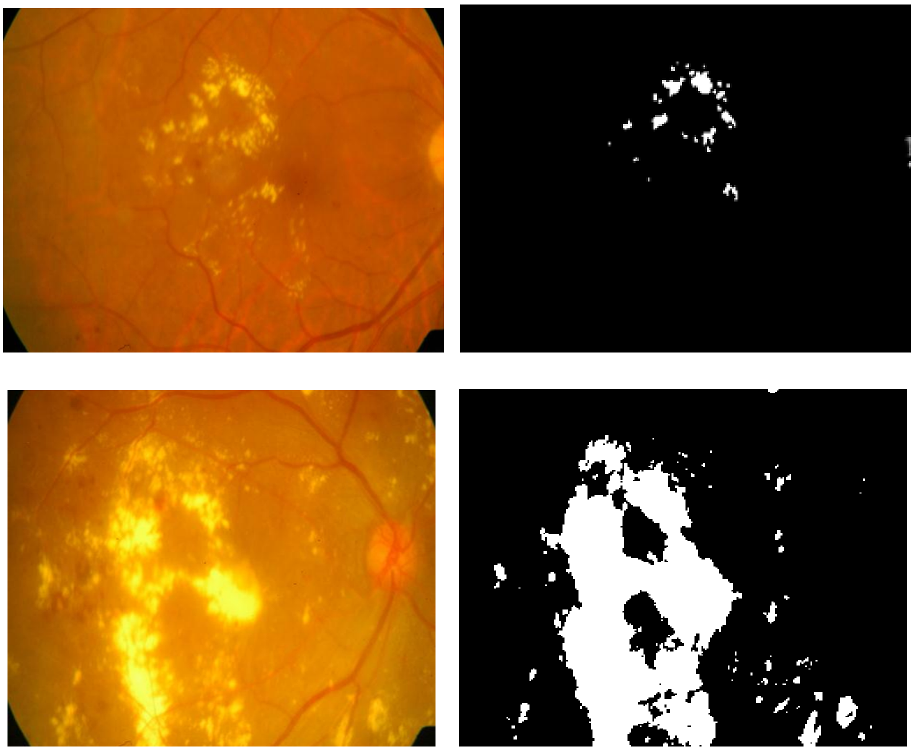

Figure 4: Fundus images and the detection of hard exudates results using SVM Classifier.

$$K(x,y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \qquad (2)$$

Where $\sigma > 0$ is a constant that defines the kernel width.

In Fig. 4 abnormal segments of hard exudates are detected using the SVM classifier. From the ROC plot in Fig. 5 it is clear that the image performance is better than the other approaches found in literature. Maximum accuracy is achieved at an operating point giving a sensitivity of 95.0% and specificity of 92.3%. The results demonstrate the best discriminating power of the texture features.

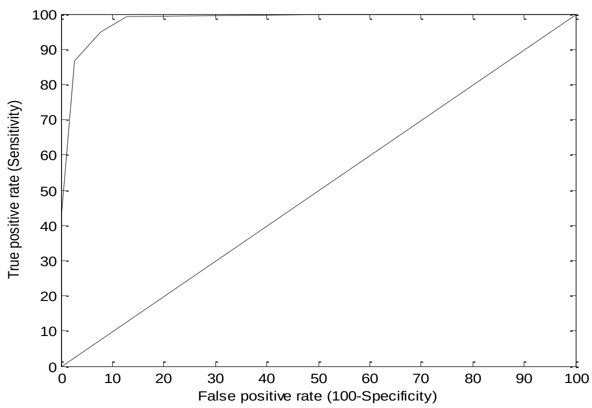

Figure 5: Receiver Operator Characteristic Curve

CONCLUSION

In this paper, Support Vector Machine toward the development of an automated computational-intelligent-based decision support system for the purpose of detecting and classifying exudates pathologies of

DR. The presentation of a complete, general CAD system approach applied to the automatic largescale screening for diabetic retinopathy is a second contribution. In contrast with much previous work, the proposed system functions on all scales—from pixels to exams and gives good performance metrics.

REFERENCES

[1] Lee SC, Lee ET, Wang Y and Klein R. Arch Ophthalmol 2005;123(6):759–764.

[2] Phillips R, Forrester J, and Sharp P. Graefe's Arch Clin Exp Ophthalmol 1993;231:90–94.

[3] Phillips R, Spencer T, Ross P, Sharp P, and Forrester J. Eye 1991;5:130–137.

[4] Timo Ojala, Matti Pietikainen and David Harwood. Pattern Recognition 1996;29(1):51-59.

[5] Ege B, Larsen O and Hejlesen O. "Detection of abnormalities in retinal images using digital image analysis," in Proc. 11th Scand. Conf. Image Process., 1999;pp. 833–840.

[6] Spencer T, Jolson J, McHardy K, Sharp P and Forrester J. Comput Biomed Res 1996;29:284–302.

[7] Wang H, Hsu H, Goh K and Lee M. "An effective approach to detect lesions in retinal images," in Proc. IEEE Conf. Comput. Vis. Pattern Recogn., Hilton Head Island, SC, 2000; 2: 181–187.

[8] Frame A, at el. Comput Biol Med 1998;28:225–238.

[9] Theo Gevers and Harro Stokman. IEEE Trans Patt Anal Mach Intell 2003;25(10):1-6.

[10] Sivanandam, SN. Sumathi and Deepa. Introduction to Neural Networks using MATLAB 6.0, Tata McGraw-Hill Publishing Company Limited, ISBN 0-07-059112-1, 2006.

[11] Oien GE and Osnes P. Proc Norw Signal Process Symp 1995, pp. 135–140.

[12] Mendonca AM, Campilho AJ and Nunes JM. Proc Int Conf Image Anal Process 1999, pp. 728–733.

[13] Autio I, Borra J, Immonen I, Jalli P and Ukkonen E. Proc Visual Imag Image Process 2005, pp. 511–517.

[14] Vapnik V. Statistical Learning Theory. New York: Wiley, 1998.

[15] Melgani F and Bruzzone L. IEEE Trans Geosci Remote Sens 2004;42(8): 1778–1790.

[16] P Clarkson and PJ Moreno. Proc IEEE Int Conf Acoustics speech Signal Process 1999; 2: 585–588.

[17] Xiwei Zhang et.al, Med Image Anal 2014; 18(7)1026-1043.

[18] Shahid Ahsan et.al. Diab Metabol Synd Clin Res Rev 2014; 8 (2): 96-101.

[19] M Usman Akram et al. Comp Biol Med 2014;45: 161-171.