# Diagnosis of retinal images using the Support Vector Machine(SVM)

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***Abstract*— Diabetic retinopathy (DR) is a condition where the retina is damaged due to fluid leaking from the blood vessels into the retina. In extreme cases, the patient will become blind. Therefore, early detection of diabetic retinopathy is crucial to prevent blindness. The main stages of diabetic retinopathy are non-proliferate diabetes retinopathy(NPDR) and proliferate diabetes retinopathy (PDR).In this work, we have proposed a computer based approach for the detection of diabetic retinopathy stage using color fundus images .The features are extracted from the raw images using the image processing techniques and fed to the support vector machine (SVM). We demonstrate a sensitivity of 97.5% for the classifier with the specificity of 100%.**

## I. INTRODUCTION

Diabetes is the commonest cause of blindness in the working age group in the developed world. Patient's sight can be affected by diabetes which causes cataracts, glaucoma, and most importantly, damage to blood vessels inside the eye, a condition known as "diabetic retinopathy". Diabetic retinopathy is a critical eye disease which can be regarded as manifestation of diabetes on the retina. The screening of diabetic patients for the development of diabetic retinopathy can potentially reduce the risk of blindness in these patients by 50%. [1]

Diabetic retinopathy can be broadly classified as nonproliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) .Therefore, regular screening of diabetic patients' retina is very important. And, automated or computer-assisted analysis of diabetic patients' retina can help eye care specialist to screen larger populations of patients.

In recent years many researchers proposed system for the automatic identification of features for diabetic retinopathy, which are useful for the treatment. These methods can only useful in subjective analysis of the diabetic retinopathy. The methods proposed in all the researches discussed above are not reliable and robust as it does not provide any objective measurement on the features.

The above discussed methods are mainly useful in analysis of the specific features on the retina, but do not provide a system as whole for the automatic detection of different stages of diabetic retinopathy. The Investigations and algorithms so far developed are unable to detect an early stage of retinopathy (NPDR) accurately [2].

We are proposing a system for automated classification of normal, NPDR and PDR retinal images by automatically detecting the blood vessels, hard exudates and texture, homogeneity. The proposed system is shown in block diagram which is shown in Fig. 1. The objective measurement such as blood vessels area, exudates area, contrast and homogeneity is computed from the processed retinal images. These objective measurements are finally fed to the support vector machine (SVM) classifier for the automatic classification.

## II. ANATOMY OF THE EYE

The human eye is similar to a camera. Light that passes through the iris is focused onto the retina through a lens. There, the visual information is encoded and transmitted to the brain through the optical nerve. In Fig. 2. A cross section of the human eye is shown with the most important anatomy labelled.

In this work the retina is the most important part of the eye. The specific vascular changes caused by diabetic retinopathy can often be detected visually by examining the retina. [3]

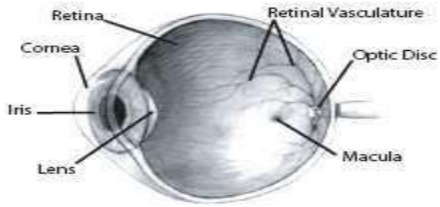



Fig.2. Cross sectional view of the right human eye

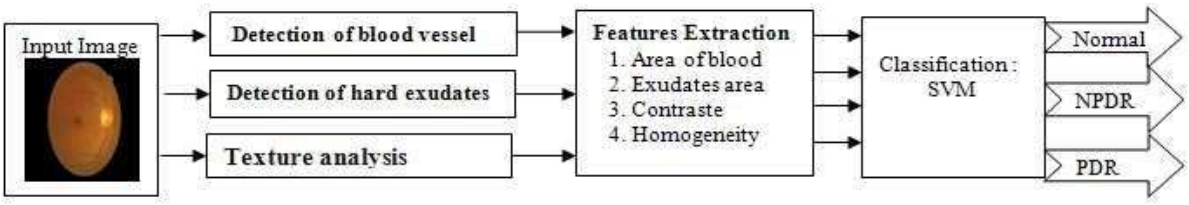



Fig .1. Proposed system for classification

## III. DIABETIC RETINOPATHY

Diabetic retinopathy is the leading cause of blindness in the working population of the western world. This eye disease is the most frequent microvascular complication of diabetes. Diabetes damages the macro- and microvascular system. Usually the eye is one of the first places where this becomes apparent. When the microvascular systemin the eye is progressively damaged, vision loss and blindness can occur (see Fig.3). The presence of diabetic retinopathy can be detected by examining the retina for its characteristic features.

One of the first unequivocal signs of the presence of diabetic retinopathy is the appearance of microaneurysms these appear as small red dots between the larger vessels of the retina. In some cases the microaneurysms will burst causing hemorrhages. As the disease and damage to the vasculature progresses larger hemorrhages will appear. In addition to leaking blood, the vessels will also leak lipids and proteins causing small bright dots called exudates to appear.

Next, small parts of the retina become ischemic deprived of blood. These ischemic areas are visible on the retina as fluffy whitish blobs called cotton wool spots. As a response to the appearance of ischemic areas in the retina the eye will start growing new vessels to supply the retina with more oxygen. These vessels, called neovascularisations, have a greater risk of rupturing and causing large hemorrhages than normal vessels. [3]

Fig 3: (a) Normal vision (b) A simulation of what someone with advanced diabetic retinopathy

A useful clinical classification according to the types of lesions detected on fundoscopy is as follows:

*A. Non-proliferative diabetic retinopathy (NPDR)*

Microaneurysms
Dot and blot hemorrhages
Hard (intra-retinal)
exudates Cotton-wool spots

*B. Proliferative diabetic retinopathy(PDR)*

Neovascularization of the retina, optic disc or iris Fibrous tissue adherent to vitreous face of retina Vitreous hemorrhage
Pre retinal hemorrhage

## IV. COMPUTER METHODS AND THEORY

### *A. Morphological image processing*

Morphological image processing is a type of processing in which the spatial form or structure of objects within an image is modified. Mathematical morphology contains two fundamental operations: morphological dilation and erosion. Dilation expands and erosion shrinks objects marked in the image. Other morphological operations are for example morphological opening and closing which are based on dilation and erosion [4].

An essential part of the dilation and erosion operations is the structuring element (SE) used to probe the input image. A structuring element is a matrix consisting of only 0s and 1s that can have any arbitrary shape and size ; Figure 4 shows diamond, disc and octagon shaped structuring element ;

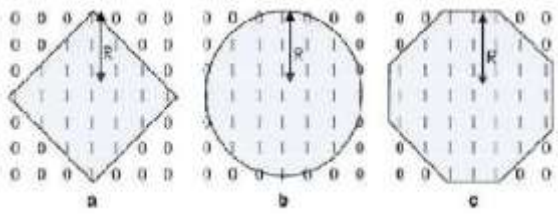


Fig 4 Structuring elements with R=3 (a) diamond (b) disc(c) octagon shaped

We will briefly review morphological operations used in this paper as the following, where f(x, y) is a finite-support grayscale image function defined on grid $Z^2$ and B is a binary structuring element. [5].

**Erosion.** $(f \ominus B)(x, y) = \min \{f(x + s, y + t)(s, t) \in B\}$.

B}.

### *B. Texture analysis*

Texture is a measure of properties such as smoothness, coarseness, and regularity of pixels in an image. Texture can also be defined as a mutual relationship among intensity values of neighboring pixels repeated over an area larger than the size of the relationship [2]. Conventional texture recognition system can be grouped into three classes: structural, statistical and spectral.

Structural texture analysis is more complex as compared to the statistical approach. Statistical approaches yield characterization of textures as smooth, coarse, grainy and so on.

Statistical algorithms are based on the relationship between intensity values of pixels; measures include entropy, contrast, and correlation based on the gray level cooccurrence matrix. In statistical methods, we describe features using a spatial gray level dependency (SGLD) matrix. For a two-dimensional image f(x,y) with N discrete gray levels, we define the spatial

gray level dependency matrix P(d, Φ) for each d and Φ, and is given by

$$P(d,\phi) = \begin{vmatrix} p_{00} & p_{01} & \cdot & \cdot & p_{0,N-1} \\ p_{10} & p_{11} & \cdot & \cdot & p_{1,N-1} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_{N-1,0} & p_{N-1,1} & \cdot & \cdot & p_{N-1,N-1} \end{vmatrix} \quad (1)$$

where

$$p_{ij} = \frac{\text{number of pixel pairs with inensity } (i,j)}{\text{total number of pairs considered}}$$

The term $P_{ij}$ is defined as the relative number of times gray level pair (i,j) occurs when pixels separated by the distance d along the angle Φ are compared. Each element is finally normalized by the total number of occurrences giving cooccurrence matrix P. A spatial gray level dependency matrix is also called a cooccurrence matrix and is shown in Eq. (1). Commonly used features that are obtained from the cooccurrence matrix are energy, entropy, correlation, inertia and local homogeneity [2].

## V. Feature Extraction

### A. Detection of the vascular tree

1) *Properties of the vessels;* The retinal blood vessels are derived from the central retinal artery and vein, which lie in the optic nerve. They are responsible for nourishing the inner parts of the retina and radiate out from the optic nerve head. [6]

2) *Vessel Detection Algorithm;* The detection of blood vessels is very important in identification of diabetic retinopathy through image processing approach.

Much has been written about the detection of vessels retinal images, Morphological image processing techniques were widely used in the detection of blood vessels. The method proposed by Walter et al in [7] was adapted in the detection of blood vessels in this work.

We work on the green channel of the RGB color space, because blood containing features appear most contrasted in this channel. This algorithm used morphological operation to smoothen the background, allowing veins, to be seen clearly. After all morphological operations, the intensity image is adjusted such that it spreads pixel intensities more evenly over the intensity range. The intensity adjustment maps the values in intensity image I(x,y) to new values in image J(x,y) such that 1% of data is saturated at low and high intensities of I(x,y). After, the background of the processed image is not as noisy as the original image and the veins can be seen clearer. The area of the features is determined by thresholding the image making the background black and the features white. We must convert a grayscale image to binary; the area is the number of white pixels [2]. Figure 5 shows the blood vessel detected images Normal and PDR fundus images.

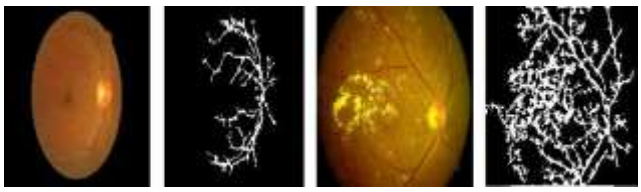


Fig.5. Results of normal and PDR Original image ;Blood vessel detection

### B. Detection of hard exudates

*1) Properties of Hard exudates and Optic disk;* The hard exudates are found in diverse sizes from puny blots to booming tracts with clear peripheries and these are the vital symptoms of Diabetic Retinopathy. Commonly the eye encompasses a fluid that is rich in fat and protein alongside blood, which oozes out from the exudates. Such a phenomenon prevents light from reaching the retina thereby leading to visual impairment. [8]

The optic disc is characterized by the largest high contrast among circular shape areas. While vessels also appear with high contrast, the size of the area is much smaller.

*2) Hard exudates detection algorithm;* Hard exudates are considered to be bright intensity regions in the retinal images. It is found from the literature that the green layer contains the most information on the brightness and structure of exudates.

Exudates detection is our main purpose; however we have to remove the optic disc prior to the process because it appears with similar intensity, color and contrast to other features on the retinal image [1].

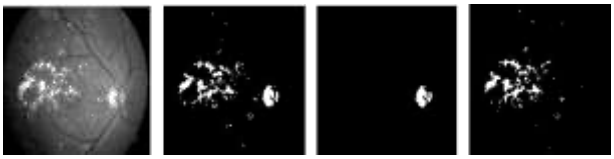
Applying a grayscale closing operator ($\varphi$) on the green channel **I** shown in fig 6(a) will help eliminate the vessels which may remain in the optic disc region. Fig. 6(b) shows a result after closing operator was applied.

$$\mathbf{I_2} = \varphi\ (\boldsymbol{B1})\ (\mathbf{I})$$

Where ***B1*** is the morphological structuring element.The resulting image $\mathbf{I_2}$ was binarized by thresholding ($\alpha 1$) .After, we remove from the binary image all connected Components (objects) that have fewer than P pixels, producing another binary image, P was chosen such that it is smaller than the maximum size of the optic disk; the optic disc occupies nearly 80×80 pixels around the optic Disc centre in the fu ndus image.

the resulting image $\mathbf{I_3}$ continent only optic disc shown in Fig.6 ©, the final result is obtained by applying a difference between the image $\mathbf{I_2}$ and the image $\mathbf{I_3}$.The resulting image is shown in Fig. 6(d).Finally the area occupied by the only detected exudates was computed by summing entire white pixels.



a b c d

Fig.6. Detection of Hard exudates

*C. Contrast& homogeneity*

The quantity of contrast and homogene ity are given, the measure of the amount of intensity variation in the image. This is given by [6].

$P_{ij}$ the elements of the co-occurrence matrix shown in Eq. (1).

## VI. CLASSIFIER USED

In the recent years, SVM classifiers have demonstrated excellent performance in a variety of p attern recognition problems. It is described in detail by Vapni k [9]

The input space is mapped into a high d imensional feature space. Then, the hyperplane that maximizes the margin of separation between classes is constructed. The points that lie closest to the decision surface are called *support vectors* and directly affect its location. When the classes are non-separable, the optimal hyperplane is the o ne that minimizes the probability of classification error.

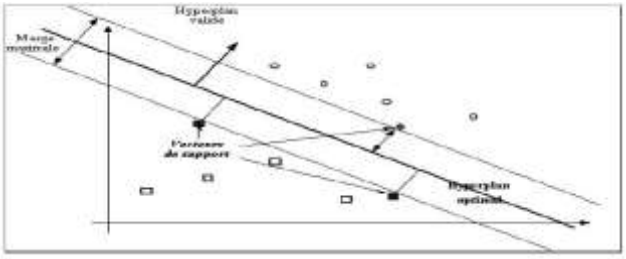


Fig. 7. Optimal Hyperplan , mximizing margin a nd support vectors

General method of construction of the O ptimal Hyperplane (HO) which separates from the data belong ing to two different classes linearly separable is as follows:Tha t is to say $H$:($W.X$) + $B$ the hyperplane which satisfies the follo wing condition

the constraint (1).This is a problem of minimization of a quadratic objective function wit1h linear constraints

By applying the principle of Lagrange, one obtains the quadratic problem of programm ing of dimension m (a number of examples) according to

$$\max \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j \, y_i y_j (x_i \cdot x_j)$$

$$\forall i, \alpha_i \geq 0$$

$$\sum_{i=1} \alpha_i y_i$$

The αi are the coefficients of La grange.

The solution for the optimum boundary w0 is a linear combination of a subset of the training data, s ∈ {1 ... N}: the support vectors. These support vectors define the margin edges and satisfy the equality $y_i[(w_o \cdot x_i) + b_o] = 1$,what is equivalent to:

$$VS = \{x_i \mid \alpha_i > 0\} \quad pour \; i = 1, \ldots, m$$

The function of classification *class* ($X$) is defines by:

$$\begin{aligned} class(x) &= sign[(w_o \cdot x) + b_o] \\ &= sign[\sum_{x_i \in VS} \alpha_i^o y_i (x_i \cdot x) + b_o] \end{aligned}$$

If *class* ($X$) is lower than 0, $X$ is in the class -1 if not it is in the class 1.

The typical kernel functions are listted below;

- Linear $k(x, x') = x \cdot x'$
- Polynomial. $k(x, x') = (x \cdot x')^d \; ou (c + x \cdot x')^d$
- Gaussian. $k(x, x') = e^{-|x - x'|^2 / \sigma}$
- Sigmoid $k(x, x') = \text{taanh}(\alpha_0 (x \cdot x') + \beta_0)$

With the origin, the SVM w ere conceived primarily for the problems with 2 classes, howe ver several approaches making it possible to extend this algorithm to the cases N classes were proposed. Generalization in the case multi-classes can be done in three different ways;The examples are one-against-one SVM, one-against-all SVM and global method.

In this work,To test the ro bustness of the SVM multi-classes in the case of automated detection of diabetic retinopathy , we used the appr oaches:Approach one- against-all.

In both cases, a Gaussian core was used for discrimination with a bandwidth σ = 1.The pa rameter of penalization C was fixed at a sufficiently high val ue so that the error of training remains weak (C = 1000).

## VII. SCREENING OF DIABETIC RETINOPATHY

At the moment the screening of diabetic retinopathy is performed by trained medical experts. In [4] Diabetes UK guidelines recommend that any procedure used for screening sight threatening diabetic retinopathy should have at least 80% sensitivity and 95% specificity; Sensitivity means the percentage of abnormal funduses classified as abnormal by the procedure. Specificity means the percentage of normal funduses classified as normal by the procedure. The higher the sensitivity and specificity values, the better the procedure. Sensitivity and specificity values can be calculated as follows

$$Sensitivity = TP/TP + FN$$

$$Specificity = TN/TN + FP$$

Where *TP*, *TN, FP* and *FN* mean true positives, true negatives, false positives, and false negatives, respectively. A screened fundus is considered as a true positive if the fundus is really abnormal and if the screening procedure also classified it as abnormal. Similarly, a true negative means that the fundus is really normal and the procedure also classified it as normal. A false positive means that the fundus is really normal, but the procedure classified it as abnormal. A false negative means that the procedure classified the screened fundus as normal, but it really is abnormal.

## VIII. MATERIALS

Our image database, to which we will refer to as the MESSIDOR database The 81 eye fundus color numerical images were acquired by 3 ophthalmologic departments using a color video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinograph with a 45 degree field of view. The images were captured using 8 bits per color plane at 1440*960, 2240*1488 or 2304*1536 pixels[10].

## IX. RESULTS

The features such as blood vessels area, hard exudates area, contrast and homogeneity (texture) corresponding to three classes were extracted using the proposed algorithms. The results of the SVM classification are shown inTable 1.

Table 2 shows the result of sensitivity, specificity, accuracy, positive predictive values for the three classes of eye images using Support vector machine(SVM) classifier. Our results show that the classifier is able to identify all the normal class. In the case, of NPDR and PDR, our classifier is able to identify their class up to 95%. The sensitivity of the system is 97.5% and specificity is 100%,

Table 1 Results of SVM classification

| Classes | No. of training | No. of testing | No. of correctly classified | classification (%) |
|---|---|---|---|---|
| **Normal** | 7 | 18 | 18 | 100 |
| **NPDR** | 7 | 19 | 17 | 89.47 |
| **PDR** | 7 | 23 | 22 | 95.65 |
| **Average** | | | | 95 |

Table 2 Results of sensitivity(Sens), specificity(Spec), positive predictive value(PPA) (of test data)

| TN | TP | FN | FP | Sens | Spec | P.P.A |
|---|---|---|---|---|---|---|
| 18 | 39 | 1 | 0 | 97.5 | 100 | 95 |

## X. DISCUSSION

An automated screening system was developed to analyse digital colour retinal images . It involves different stages of the non-proliferative DR and proliferative DR class too [11]. The algorithm achieved a sensitivity of 90% and specificity of 100.

A computer system was developed to identify the normal, mild DR, moderate DR, severe DR and prolific Drin [12] This algorithm demonstrated a specificity of 88% and a resulting sensitivity of 82% in detecting diabetic retinopathy.

Q. Li et al. have proposed a method for screening DR and distinguishing PDR from NPDR automatatically through color retinal images using morphlogical reconstruction in[13]. The algorithm achieved a sensitivity of 80;5% and specificity of 90.8%.

Jagadish et al [2] have proposed a computer based approach for the detection of diabetic retinopathy stage using fundus images. This system showed a sensitivity of 90% and specificity of 100% for all the test images.

Our system is more comprehensive as compared to the other works discussed so far. Our system can automatically detect the three classes with an average efficiency of 95%.It also, detects diabetic retinopathy in an early stage (NPDR) with an sensitivity of 97.5% and specificity of 100%%and hence helps in preventing the loss of vision.

In this work, we have used 81 fundus images. The clinical efficiency of our system can be improved by taking more retinal images under uniform lighting.

## XI. CONCLUSIONS

In this work we have investigated and proposed a computer-based system to identify normal, NPDR and PDR. The system proposed demonstrated a classification accuracy of 95%, sensitivity of 97.5% and specificity of 100%. The results demonstrated here indicate that the system can help the ophthalmologist to detect diabetes
retinopathy at the early stage.

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