Diabetic Retinopathy Detection

Using SVM and KNN

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Abstract

Diabetic retinopathy, also known as diabetic eye disease, is a medical condition in which damage occurs to the retina due to diabetes and is a leading cause of blindness. As diabetes progresses, the person's vision start getting blurry due to diabetic retinopathy. In this paper, to diagnose diabetic retinopathy, Support Vector Machine (SVM) and k-Nearest Neighbours (kNN) are used and their achieved accuracies are compared. It is observed that SVM has an accuracy of 96.62% and KNN has an accuracy of 94.38 %. This clearly indicates that the SVM model is better than kNN.

Keywords—

Diabetic Retinopathy, Support Vector Machine, k-Nearest Neighbours

1. INTRODUCTION

Diabetic retinopathy occurs when changes in blood glucose levels cause changes in retinal blood vessels. In some cases, these vessels will swell up (macular oedema) and leak fluid into the rear of the eye.In other cases, abnormal blood vessels will grow on the surface of the retina.Unless treated, diabetic retinopathy can gradually become more serious and progress from 'background retinopathy' to seriously affecting vision and can lead to blindness.Diabetes is a group of metabolic diseases in which a person has high blood sugar, either because the body does not produce enough insulin, or because cells do not respond to the insulin that is produced. The risk of the disease increases with age and therefore, middle aged and older diabetics are prone to Diabetic Retinopathy. Non proliferative diabetic retinopathy is an early stage of diabetic retinopathy. In this stage, tiny blood vessels within the retina leak blood or fluid. The leaking fluid causes the retina to swell or to form deposits called exudates. Proliferative diabetic retinopathy,PDR is an attempt by the eye to grow or re-supply the retina with new blood vessels (neovascularization), due to widespread closure of the retinal blood supply.

SYMPTOMS

Symptoms may only become noticeable once the disease advances, but the typical symptoms of retinopathy to look out for include:

A. Sudden changes in vision / blurred vision.

B. Eye floaters and spots.

C. Double vision.

D. Eye pain.

PRECAUTIONS

The risk of developing diabetic retinopathy can be lessened through taking the following precautions:

A. Taking dialated examination once a year

B. Managing diabetes strictly through medicine, insulin,diet and exercise

C. Test blood sugar level regularly

D. Test urine for ketone levels regularly

2. PROPOSED SYSTEM

We reserved 33% of each dataset for testing and then performed 10-fold cross validation on the remaining 73% of the dataset.

The evaluation of the proposed automated diagnosis system of diabetic retinopathy has been performed by using a set of 89 images which is a combination of normal (healthy) and diseased eyes. The image which is of size 1152×1500 is converted to gray scale image. After that, adaptive histogram equalization is applied to improve the contrast of the image. Then, DWT is applied. Then, Gabor Kernel is applied to enhance blood vessels and retinal pores in the image. Finally, k-Means Clustering is used to separate the eye images into two sections. After pre-processing of images is completed, Modeling Techniques like SVM and kNN are used and their performances are compared. Finally, the images are classified into healthy and affected eyes. The remainder of this paper is organized as follows. Section 3 describes the preprocessing of images. Section 4 describes the classification of DR disease using Support Vector Machine.Section 5 explains K-Nearest Neighbors. Section 6 gives the experimental results. Section 8 gives the conclusion.

3. PREPROCESSING OF IMAGES

The technique of pre-processing is very important step in the process as due to it we get the proper illumination of the images as well as it gives us the desired result at different steps so that we can work properly on the image to get our desired result . The techniques for preprocessing include

a)Gray scale Conversion

b)Adaptive Histogram Equalization

c)Discrete Wavelet Transform

d) Gabor Kernel and K-Means Clustering for segmentation of blood vessels.

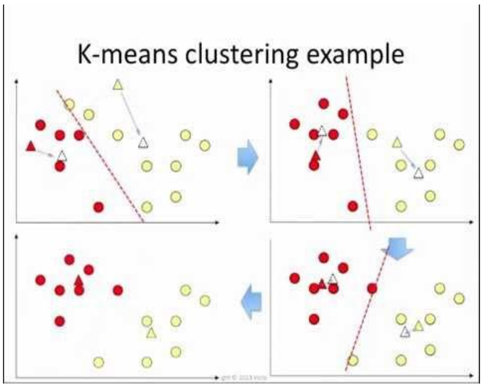
The acquired image resolution is 1152×1500 in PNG format. The color image of an eye is taken as input image and is converted to a grayscale image.

Adaptive histogram equalization which is used to improve contrast in images, is applied to the grayscale converted eye image.Since after the grey scale process there are some part of the images which are not clearly visible, in other words they are dark.So in order to have a clear image we use Adaptive Histogram Equalisation,it brightnes the part of the image which is low contrast and also the part of the image which are of high contrast is also taken care of so that the image is not damaged. As a result of this adaptive histogram equalisation, the dark area in the input eye image that was badly illuminated has become brighter in the output eye image while the side that was highly illuminated remains or reduces so that the whole illumination of the eye image is same.

A discrete wavelet transform (**DWT**) is any wavelet transform for which the wavelets are discretely sampled.
As with other wavelet transforms, a key advantage about it is that it has over **Fourier transforms** is temporal resolution: it captures both frequency *and* location information (location in time).
The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Discrete Wavelet Transform (DWT), which is based on sub band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet ψ(t) called **mother wavelet** by **dilations and shifting**. The **mother wavelet** used to generate all the basis functions is designed based on some desired characteristics associated with that function.
[cA,cH,cV,cD] = dwt2(X,'wname') computes the approximation coefficients matrix cA and details coefficients matrices cH, cV, and cD (horizontal, vertical, and diagonal, respectively), obtained by wavelet decomposition of the input matrix X where X is the given input eye image after applying adaptive histogram equalization. The 'wname' string contains the wavelet name. In this paper, Haar wavelet is used.

After this, the Gabor Kernel is employed.
ts impulse response is defined by a sinusoidal wave (a plane wave for 2D Gabor filters) multiplied by a Gaussian function Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually. The Fourier transform has been the most commonly used tool for analyzing frequency properties of a given signal, while after transformation, the information about time is lost and it's hard to tell where a certain frequency occurs. To solve this problem, we can use kinds of time-frequency analysis techniques to represent a 1-D signal in time and frequency simultaneously. There is always uncertainty between the time and the frequency resolution of the window function used in this analysis since it is well know that when the time duration get larger, the bandwidth becomes smaller. Several ways have been proposed to find the uncertainty bound, and the most common one is the multiple of the standard deviations on time and frequency domain. Among all kinds of window functions, the Gabor function is proved to achieve the lower bound and performs the best analytical resolution in the joint domain. This function is a Gaussian modulated by a sinusoidal signal.

***k*-means clustering** is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. *k*-means clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells.
K-Means Clustering is a method of clustering which allows one piece of data to belong to two or more clusters. Here it is used to segment the input eye image and detect the blood vessels. Information about blood vessels can be used in grading disease severity or as part of the process of automated diagnosis of diseases with ocular manifestations.



Equations—

1. Adaptive Histogram Equalization

$$P_n = 255\left(\frac{[\varphi_w(p)-\varphi_w(Min)]}{[\varphi_w(Max)-\varphi_w(Min)]}\right) \quad (1)$$

Where

$$\varphi_w(p) = \left[1+\exp\left(\frac{\mu_w - p}{\sigma_w}\right)\right]^{-1} \quad (2)$$

and Max and Min are the maximum and minimum intensity values in the whole eye image while μ_w indicates the local window mean and σ_w indicates standard deviation which are defined as:

$$\mu_w = \frac{1}{N^2} \sum_{(i,j)\in(k,l)} P(i,j) \qquad (3)$$

$$\sigma_w = \sqrt{\frac{1}{N^2} \sum_{(i,j)\in(k,l)} (P(i,j) - \mu_w)^2} \qquad (4)$$

2. Discrete Wavelet Transform

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right) \qquad (5)$$

Where a is the scaling parameter and b is the shifting parameter.

3. Gabor Kernel

$$\sigma_t^2 = \frac{\int t^2 |x(t)|^2 dt}{\int |x(t)|^2 dt}, \sigma_f^2 = \frac{\int f^2 |X(f)|^2 df}{\int |X(f)|^2 df} \qquad (6)$$

$$\sigma_t \times \sigma_f \geq \frac{1}{4\pi} \qquad (7)$$

$$\varphi(t) = exp(-\alpha^2 t^2)\, exp(j2\pi f_0 t) \qquad (8)$$

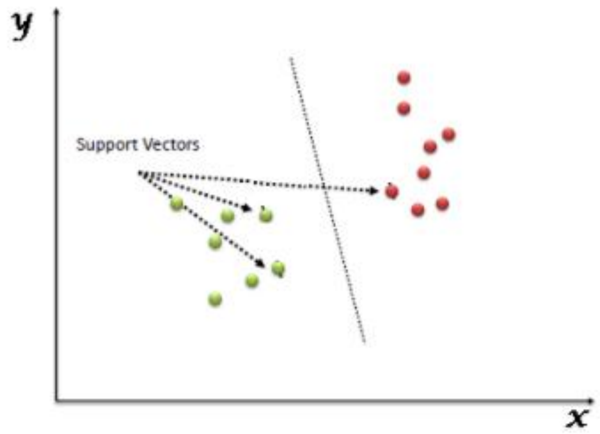
$$\Phi(f) = \sqrt{\frac{\pi}{\alpha^2}} exp\left(-\frac{\pi^2}{\alpha^2 (f - f_0)^2}\right) \qquad (9)$$

Where α determines the sharpness and f_0 is the modulated center frequency of $\varphi(t)$, and $\Phi(f)$ is its Fourier transform.

4. SUPPORT VECTOR MACHINE

Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well

Support Vectors are simply the co-ordinates of individual observation. Support Vector Machine is a frontier which best segregates the two classes (hyper-plane/ line).



5. k-NEAREST NEIGHBORS

In pattern recoginition, the ***k*-nearest neighbors algorithm** (***k*-NN**) is a non paramrtric method used for classification and regression.[1]In both cases, the input consists of the *k* closest training examples in the feature space. The output depends on whether *k*-NN is used for classification or regression:

- In *k-NN classification*, the output is a class membership. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its *k* nearest neighbours (*k* is a positive integer, typically small). If *k* = 1, then the object is simply assigned to the class of that single nearest neighbour.
- In *k-NN regression*, the output is the property value for the object. This value is the average of the values of its *k* nearest neighbours.

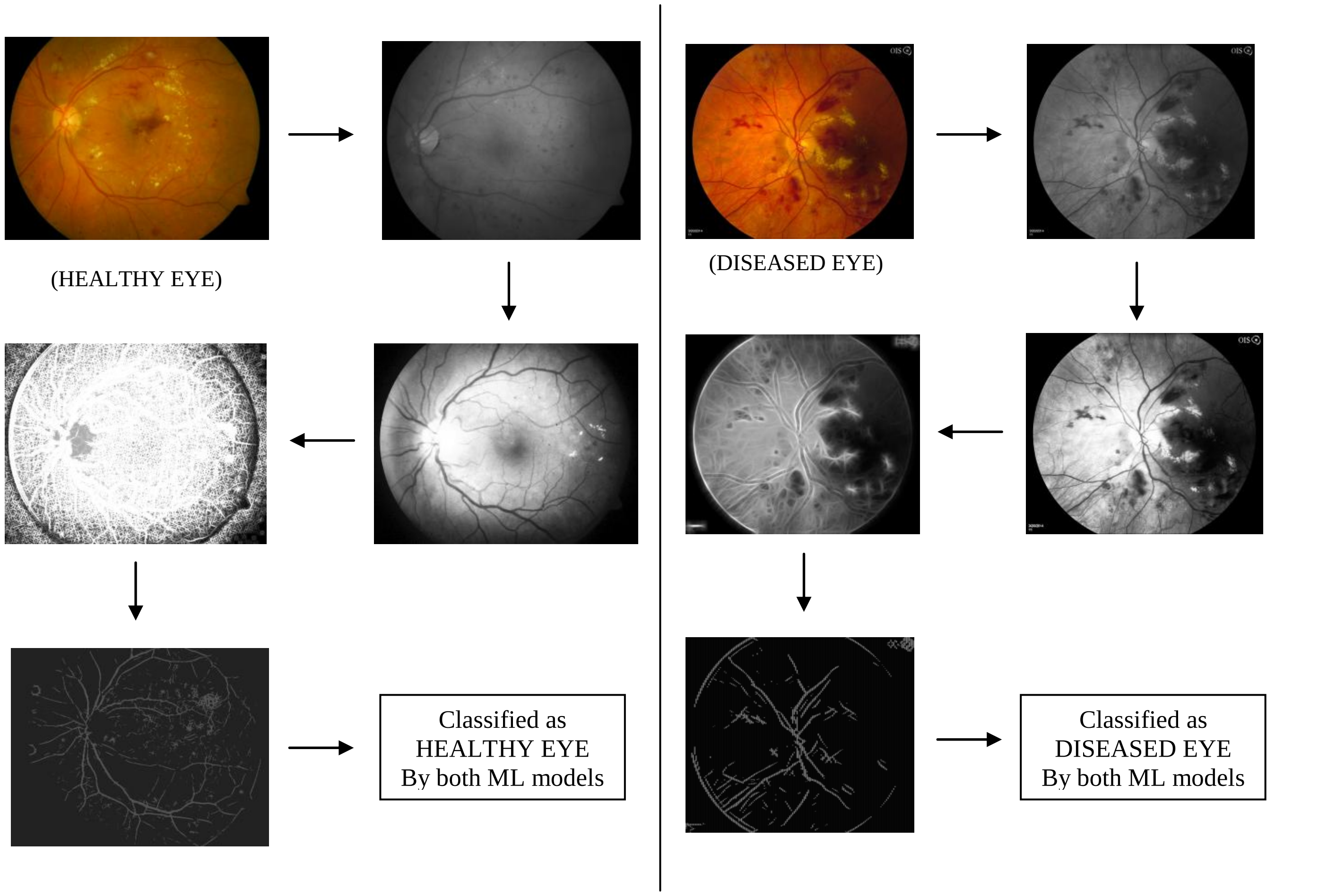
k-NN is a type of instance-based learning, or lay learning, where the function is only approximated locally and all computation is deferred until classification. The *k*-NN algorithm is among the simplest of all machine learning algorithms.

. One way to improve its efficiency is to find some representatives to represent the whole training data for classification, viz. building an inductive learning model from the training dataset and using this model (representatives) for classification. There are many existing algorithms such as decision trees or neural networks initially designed to build such a model. One of the evaluation standards for different algorithms is their performance. As kNN is a simple but effective method for classification and it is convincing as one of the most effective methods, it motivates us to build a model for kNN to improve its efficiency whilst preserving its classification accuracy as well. If we use Euclidean distance as our similarity measure, it is clear that many data points with the same class label are close to each other according to distance measure in many local areas.

6. EXPERIMENT RESULT

S.No	ML Model	Accuracy
1	SVM	96.62%
2	kNN	94.38%

7. EXPERIMENT OBSERVATIONS



8. CONCLUSION

Firstly, all input images were pre-processed using Grayscale conversion, Adaptive Histogram Equalization, Discrete Wavelet Transform, Gabor kernal and K means clustering. Then, these processed images are fed into the 2 ML Models and the corresponding results are compared.
So, at the end, we are able to classify that a person is suffering from DR or NOT. All the two techniques used for the classification were good in performance, but SVM gives better accuracy than KNN which is evident from the obtained results. Thus this work proved to be a fairly good way to detect Diabetic Retinopathy in a person.

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References—

[1] Diabetes mellitus: http://en.wikipedia.org/wiki/Diabetes_mellitus

[2] Advanced Vision Care: http://www.advancedvisioncare.com/conditions.php

[3] R.Sivakumar, G.Ravindran, M.Muthayya, S.Lakshminarayanan, C.U. Velmurughendran, Diabetic Retinopathy Analysis, 2005.

[4] Frederick L. Ferris et al, “Treatment of Diabetic Retinopathy”, NEJM, 1999.

[5] Rafael Simó, Cristina Hernández, “Advances in the Medical Treatment of Diabetic Retinopathy”, NCBI, 2009.

[6] Vallabha,D., Dorairaj, R., Namuduri K. and Thompson., H, "Automated Detection and Classification of Vascular Abnormalities in Diabetic Retinopathy", IEEE, 2004.

[7] R.Sivakumar, G.Ravindran, M.Muthayya, S.Lakshminarayanan, C.U. Velmurughendran, Diabetic Retinopathy Classification‖, IEEE, 2003.

[8] R. Priya, P. Aruna, “SVM and Neural Network based Diagnosis of Diabetic Retinopathy”, IJCA, 2012.

[9] Wei-lun Chao, Gabor wavelet transform and its application, R98942073, unpublished.

[10] Hemant P. Chaudhari, Amol D. Rahulkar, Chetankumar Y. Patil, “Segmentation of Retinal Vessels by the Use of Gabor Wavelet and Linear Mean Squared Error Classifier”, IJEERT, 2014.