Diabetic Retinopathy Detection

Using SVM and KNN

Prakkash Manohar
Student, CSE
IIIT Sri City
Chittoor

Abstract

Diabetic retinopathy (DR) is an eye disease caused by the complication of diabetes and we should detect it early for effective treatment. As diabetes progresses, the vision of a patient may start to deteriorate and lead to diabetic retinopathy. First we pre-process the image to enhance the required features for the ML techniques to work, which includes:

1. Grayscale Conversion
2. Adaptive Histogram Equalization
3. Discrete Wavelet Transform
4. Gabor Kernel followed by k-Means Clustering

Next, we use this pre-processed image as an input to our ML algorithms. Here, we are using 2 Machine Learning Algorithms to diagnose diabetic retinopathy, namely, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) and then, we compare the results of both these algorithms. We observe that SVM has an accuracy of 96.62% and KNN has an accuracy of 94.38%.

Keywords—

Diabetic Retinopathy, Support Vector Machine, K-Nearest Neighbors

1. INTRODUCTION

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. Diabetic retinopathy is one of the common complications of diabetes. It is a severe and widely spread eye disease. It damages the small blood vessels in the retina resulting in loss of vision. 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.

2. PROPOSED SYSTEM

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 describes the experimental results. Sections 7 and 8 give the observations and conclusion respectively. Figure 1. gives the block diagram of the proposed system for diagnosis of Diabetic Retinopathy.

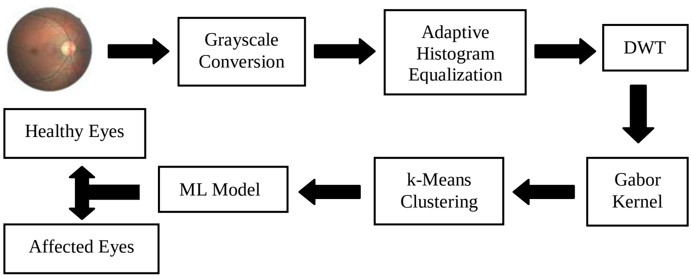


Figure 1: Process Flow for Diabetic Retinopathy Detection

3. PREPROCESSING OF IMAGES

In detecting abnormalities associated with the eye image, the images have to be pre-processed in order to correct the problems of uneven illumination problem. The techniques for preprocessing include Gray scale Conversion, Adaptive Histogram Equalization, Discrete Wavelet Transform, 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.

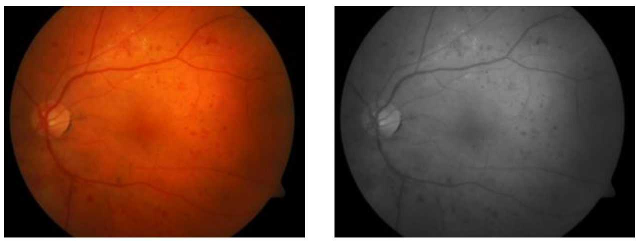


Figure 2: a) shows original colored image of eye. b) shows corresponding grayscale image.

Adaptive histogram equalization which is used to improve contrast in images, is applied to the grayscale converted eye image. Consider a running sub image W of N×N pixels centered on a pixel P(i,j), the image is filtered to produce another sub image P of (N×N) pixels according to the equation below:

$$\boldsymbol{P}_n = 255\left(\frac{[\varphi_w(p)-\varphi_w(Min)]}{[\varphi_w(Max)-\varphi_w(Min)]}\right) \qquad (1)$$

Where

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

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

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

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

As a result of this adaptive histogram equalization, 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. 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:

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

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

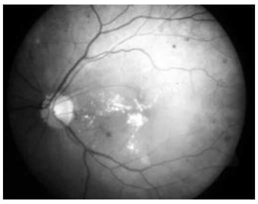


Figure 2: c) shows eye image after pre-processing upto DWT

After this, the Gabor Kernel is used whose description follows. 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:

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

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

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 and is as follows:

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

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

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

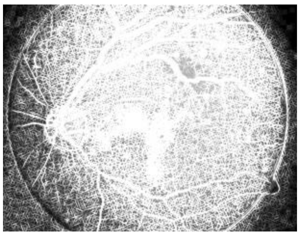


Figure 2: c) shows eye image after feeding into Gabor Kernel

Next follows, k-Means Clustering which is a method of clustering that 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.

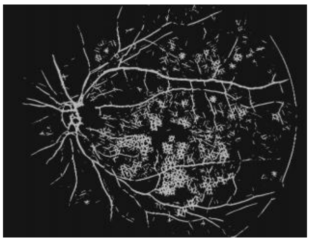


Figure 2: d) shows completely pre-processed eye image

4. SUPPORT VECTOR MACHINE

Support vector machine training process is applied to analyze training data to find an optimal way to classify images into their respective classes namely Normal and Diseased. Classification parameters are calculated using support vector machine learning. The training process analyzes training data to find an optimal way to classify images into their respective classes. The training data should be sufficient to be statistically significant. The support vector machine learning algorithm is applied to produce the classification parameters according to calculated features. The derived classification parameters are used to classify the images.

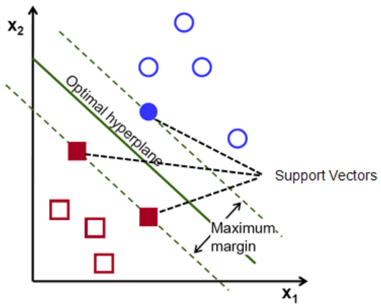


Figure 3: A training dataset, with 2 classes {square and circle} distributed in 2-dimensional data space and the optimal hyperplane separating the 2 classes is shown above.

The image content can be discriminated into the various categories in terms of the designed support vector classifier. To fit nonlinear curves to the data, SVM make use of a *kernel function* to map the data into a different space where a hyperplane can be used to do the separation. SVM can be applied to non-linear classification using nonlinear kernel functions to map the input data onto a higher dimensional feature space in which the input data can be separated with a linear classifier.

5. K-NEAREST NEIGHBORS

KNN is a case-based learning method, which keeps all the training data for classification. 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.

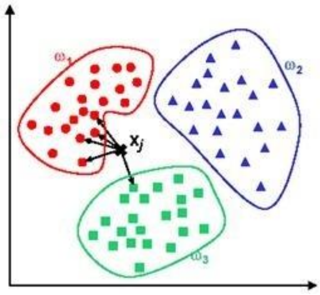


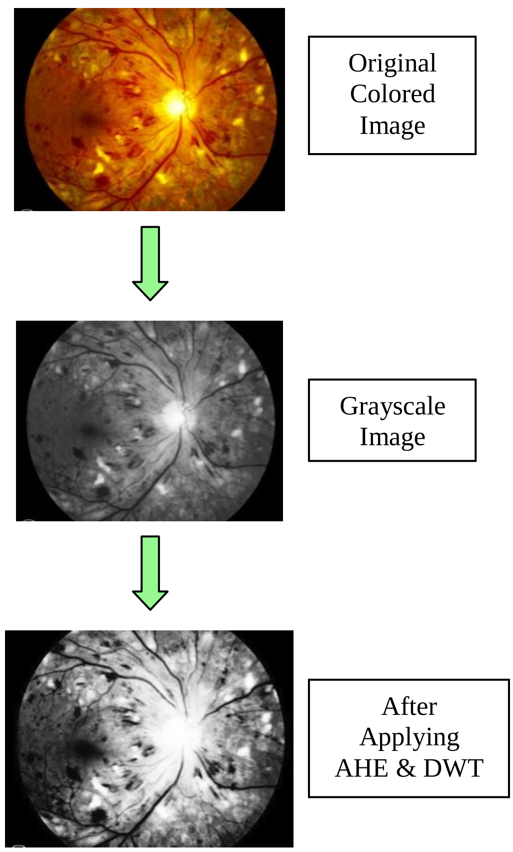
Figure 4: A training dataset, including data points with three classes, {square, circle and triangle} is distributed in 2-dimensional data space.

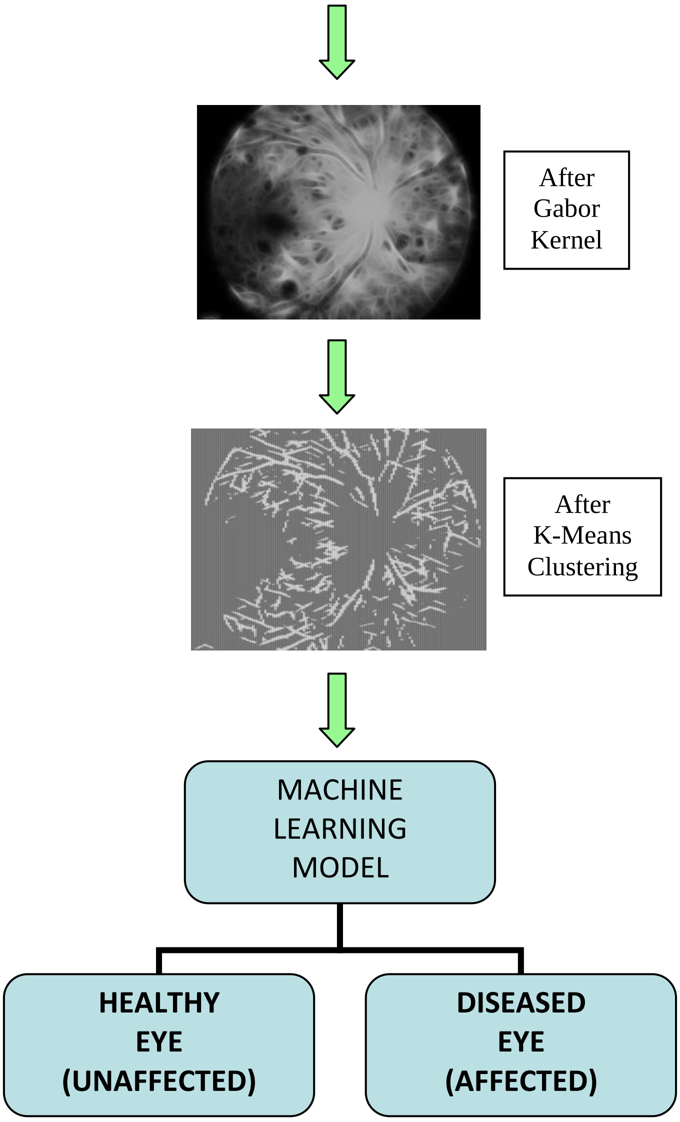
If we use Euclidean distance as our similarity measure, it is clear that many data points with the same class label are close to each other according to distance measure in many local areas.

6. RESULT

The Experiment shows that **SVM gives an accuracy of 96.62%** whereas **kNN gives an accuracy of 94.38%**. So, we infer that SVM outperforms KNN.

7. OBSERVATIONS





8. CONCLUSION

Diabetic Retinopathy is detected by analyzing coloured eye images. The input retinal images are of poor quality. So they were pre-processed using Grayscale conversion, Adaptive Histogram Equalization, Discrete Wavelet Transform, Gabor kernel and k-means clustering. As an achievement of this work, we are able to detect if a person has Diabetic Retinopathy or not. Both the techniques used for classification were good in performance, but SVM is more efficient than KNN. Thus this work has given a successful Diabetic Retinopathy Diagnosing method which helps to diagnose the disease in early stage which mutually reduces the manual work.

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