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Diabetic Retinopathy Classification using ANN

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Aim: The main motivation of this algorithm is to process the image and to diagnose diabetic retinopathy from images of retina. The preprocessing step equalizes the uneven illumination associated with fundus images and also removes noise present in the input iris image. Segmentation stage clusters the image into two distinct classes while the Disease Classifier stage was used to distinguish between candidate either Normal stage or else Diabetic retinopathy symptoms detected (abnormal) stage. This algorithm was totally tested and implemented 10 fundus images. Also calculated the TPR, FPR, Accuracy and the classification results are tabulated.

Keywords: ANN Classification, Morphological operation, Diabetic retinopathy.

Introduction

Diabetic retinopathy (DR) is one of the most important causes of visual loss worldwide and is the principal cause of impaired vision in patients between 25 and 74 years of age. Visual loss from DR may be secondary to macular edema (ME; retinal thickening and edema involving the macula), hemorrhage from new vessels, retinal detachment, or neovascular glaucoma.

DR is often asymptomatic until the very late stages. Because the rate of progression may be rapid and therapy can be beneficial for visual improvement, prevention of further visual loss, and reduction in the rate of disease progression, it is important to screen patients with diabetes regularly for the development of retinal disease.

Diabetic retinopathy (DR) is divided into two major forms: non-proliferative and proliferative, respectively named for the absence or presence of abnormal new blood vessels emanating from the retina. DR can be further classified by severity. Diabetic macular edema (ME) may develop at any point along the spectrum of mild non-proliferative disease to proliferative diabetic retinopathy. These designations have been useful for analysis of treatment efficacy in the literature and general indicators for treatment strategies. However, each patient with DR has a unique combination of findings, symptoms, and rate of progression, which necessarily requires an individualized approach to treatment in the effort to preserve vision.

Literature Survey

There have been an increase in the use of digital image processing techniques for the screening of DR after it was recommended as one of the method for screening DR at the conference on DR [1]. With this increase more work have been done to improve some of the existing screening method while new methods have also been introduced in order to really increase the sensitivity and the specificity of this method. Sensitivity refers to the percentage of abnormal fundus image classified as abnormal by the method

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while specificity can be defined as percentage of normal fundus image classify as normal. The higher these two factors the better the method. Most of the available work done can generally be categorized into screening of BDR and PDR while diagnosis of SDR have been left for the ophthalmologist. However only few work have really been done in the detection of microaneurysm and exudates, most work done are in vascular abnormalities detection using color fundus images. In this section, some of these past works are review and the results obtained are also discussed.

Vallabha et al in their work titled automated detection and classification of vascular abnormalities in diabetic retinopathy [8] applied the use of scale and orientation of selective Gabor filter to detect and classify the retina images into mild or severe case. Scale and angle analysis were used because of its ability to distinguish images by virtues of its variation across scales and orientation. The input image is first filtered through Gabor filter banks. The banks consist of several filters tuned to specific scales and orientation and the operation is performed in Fourier domain. The output of which is then analyzed. Detection of NPDR (PDR) is done by analysing the width of the blood vessels. The presence of one local maxima in the plot of energy vs. orientation for more than 100 test images signify the presence of mild to NPDR (PDR) while the presence of more than one local maxima signify severe PDR. This method only signifies the presence of BDR and PDR but does not specify the co- ordinates nor the actual spots or actual disease type. The specificity and sensitivity of this method were not discussed in work done nor do they use a full scale image, instead part of the images of size 256 x 256 pixels were used.

Proposed Algorithms

The aim of this algorithm to develop a system that will identify the patients with Diabetic Retinopathy. And also, either used the color image or gray level image used from the retina of the patient. These types of Iris images are called as fundus images. The different diabetic retinopathy diseases the either fall between the normal or abnormal stages of the diseases. The Early-stage identification is very useful for the Ophthalmologist.

The input image to the preprocessing stage either used gray scale image or else color Iris image. The preprocessing stage to rectify the problem of illumination variation that occurs when taken the pictures. Remaining problems are rectified by using the Morphological operation, Histogram equalization.

The output of this algorithm is passed to the segmentation step to separate the background pixel from the exudates and the vein networks using K-means clustering algorithm with two cluster centers. The exudated and the vein networks class centers also contain some noisy pixels that were over enhances during the Pre-processing stage and will be removed by using the filters. After removal of noise that were over enhanced during the preprocessing stage and will be removed during the next stage called as Disease Classifier stage[8-10].

The ANN classification used to classify whether the input Iris images are Normal or Abnormal stage.

At the Preprocessing step matches the unequal illumination associated with fundus images and also removes noise present in the input Iris image. Then the segmentation step groups or clusters the Iris image into two different classes while the Disease Classifier stage was used to distinguish between candidate lesions and other information. These algorithms step are used to recognized and also classify the disease, whether Normal or Diabetic retinopathy image.

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International Journal of Mechanical Engineering

Morphological Operations

In automatic object detection and machine vison the Morphological operation playing a vital role. This operation characterized by Erosion, Dilation, opening and closing.

a) Dilation

Dilation works exactly opposite to erosion. It “dilates” or expands the boundaries of the foreground object which in turn increases the size of the object in the image. This is useful to join broken parts of the foreground object.

Dilation is a process that thickens objects in a binary image. The extent of this thickening is controlled by the Structuring Element (SE) which is represented by a matrix of 0s and 1s. Mathematically, dilation operation can be written in terms of set notation as below

$$A \oplus A_s = \{z \mid (A_s^{'})_z \cap A \neq \Phi\} \qquad (1)$$

Where Φ is an empty element and A_s is the structuring element. The dilation of A by A_s is the set consisting of all structuring element origin locations where the reflected and transmitted A_s overlaps at least some portions of A. Dilation operation is commutative and associative.

b) Erosion

The pixels at the boundary of the foreground object are removed. It reduces the size of the object in the image. Erosion shrinks or thins the objects in a binary image by the use of structuring element. The mathematical representation of erosion is as shown below.

$$A \ominus A_s = \{z \mid (A_s)_z \cap A^c \neq \Phi\} \qquad (2)$$

c) Opening and Closing

The Closing is the opposite of Opening, which means that dilation is applied first followed by erosion. This is useful for joining or filling small spots that are present in the foreground object, while retaining the size of the object.

The Opening operation is used in noise removal. It is done by first applying the erosion operation, followed by the dilation operation. The erosion operation first removes all the small noisy areas from the image and then dilation is applied to restore the original size of the object. In image processing, dilation and erosion are used most often and in various combinations. An image may be subjected to series of dilations and or erosions using the same or different SE. The combination of these two principles leads to morphological image opening and morphological image closing. Morphological opening can be described as an erosion operation followed by a dilation operation. Morphological opening of image X by Y is denoted by X O Y, which is erosion of X by Y followed by dilation of the result obtain by Y closing and opening

$$X \circ Y = (X \oplus Y) \ominus Y \qquad (3)$$

$$X \bullet Y = (X \ominus Y) \oplus Y \qquad (4)$$

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International Journal of Mechanical Engineering

Morphological closing can also be described as dilation operation followed by erosion operation. Morphological Closing of Image X by Y is denoted by $X \circ Y$, which is dilation of X by Y followed by erosion of the result obtained by Y.

Histogram Equalization

One of the problems associated with fundus images is uneven Illumination. Some areas of the fundus images appear to be brighter than the other. Areas at the centre of the image are always well illuminated, hence appears very bright while the sides at the edges or far away are poorly illuminated and appears to be very dark. In fact the illumination decreases as distance form the centre of the image increase. Many methods were tried in resolving this problem of un-even illumination, among which are the use of Naka Rushton method and Adaptive Histogram Equalization Method (AHEM). AHEM gives better performance, higher processing speed and work well for all images of different sizes, hence the reason for it being used as method of correcting uneven illumination.

Adaptive Histogram Equalization:

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. However, AHE has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) prevents this by limiting the amplification

a) Naka Rushton Method

The filtering effect is based on the method called Naka Rushton method and the equation is as given below

$$O(i,j) = \frac{I(i,j)}{I(i,j) + \mu_{window}} \tag{5}$$

where $O(i,j)$ is the transformation result, $I(i,j)$ is the original image and μ_{window} is the average of the chosen exploration window. Using this method, a grey level compression of the image was produced with high contrast between the background and the objects information contained there in. The grey level represented in the original image was compressed, though it works well for small parts of image but doesn't perform well for images with complete size. Aside this, a lot of noise was added to the image using this method and this leads to false and poor segmentation stage. Also in the work done by Bevilacqua et all, it was only of interest to find vascular features and not all the features associated with fundus images so a more robust method, with less noisy output and fast processing speed is needed for the large images used for this work hence the need for Adaptive Histogram Equalization Method (AHEM)[1-8].

b) Adaptive Histogram Equalization

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International Journal of Mechanical Engineering

The main objective of this AHE method is to define a point transformation within a local fairly large window with the assumption that the intensity value within it is a stoical representation of local distribution of intensity value of the whole image. The local window is assumed to be unaffected by the gradual variation of intensity between the image centres and edges. The point transformation distribution is localised around the mean intensity of the window and it covers the entire intensity range of the image. Consider a running sub image W of N X N pixels centred on a pixel P (i,j) , the image is filtered to produce another sub image P of (N X N) pixels according to the equation below

$$P_n = 255\left[\frac{[\phi_w(p)-\phi_w(\min)]}{[\phi_w(max)-\phi_w(\min)]}\right] \quad (6)$$

Where

$$\phi_w(p) = \left[1+\exp\left(\frac{\mu_w - p}{\sigma_w}\right)\right]^{-1} \quad (7)$$

and Max and Min are the maximum and minimum intensity values in the whole image, while

μ_w and σ_w indicate the local window mean and standard deviation which are defined as:

As a result of this adaptive histogram equalization, the dark area in the input image that was badly illuminated has become brighter in the output image while the side that was highly illuminated remain or reduces so that the whole illumination of the image is same. It is worthy of mentioning that this method also used overlap mean in the final buildup of the image.

Median Filter:

The median filter is a nonlinear digital filtering technique often used to remove noise. Median filtering is very widely used in digital image processing because it preserves edges while removing noise. It replaces the pixel value by the median value in the neighborhood. The main principal function is to force distinct gray level points to be more like their neighbors. The below figure1 is an example for medial filter.

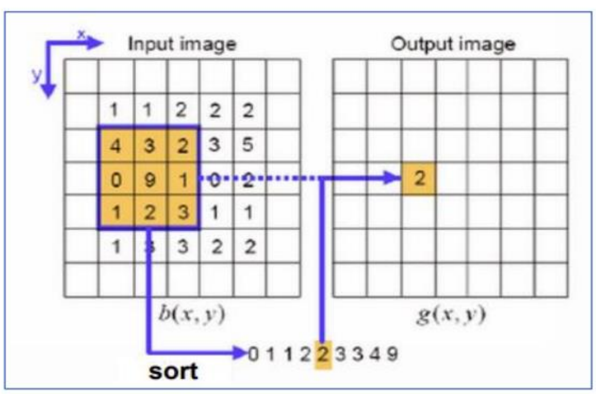

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Figure 1. Example for Median Filter

$$Median\left(f_1(x) + f_2(x) \right) \neq Median(f_1(x)) + Median(f_2(x)) \tag{8}$$

K-Means Clustering Algorithm:

K-means clustering algorithm computes the centroids and iterates until it finds optimal centroid. It assumes that the number of clusters are already known. It is also called flat clustering algorithm. The number of clusters identified from data by algorithm is represented by 'K' in K-means [11-12].

In this algorithm, the data points are assigned to a cluster in such a manner that the sum of the squared distance between the data points and centroid would be minimum. It is to be understood that less variation within the clusters will lead to more similar data points within same cluster.

Working of K-Means Algorithm: To understand the working of K-Means clustering algorithm with the help of following steps:

Step 1: First, need to specify the number of clusters, K, need to be generated by this algorithm.

Step 2: Next, randomly select K data points and assign each data point to a cluster. In simple words, classify the data based on the number of data points.

Step 3: Now it will compute the cluster centroids.

Step 4: Next, keep iterating the following until to find optimal centroid which is the assignment of data points to the clusters that are not changing any more.

Step 5: First, the sum of squared distance between data points and centroids would be computed.

Step 6: Now, to assign each data point to the cluster that is closer than other cluster (centroid).

Step 7: At last compute the centroids for the clusters by taking the average of all data points of that cluster.

Initialize cluster centroids $\mu_1, \mu_2, ...\mu_k \in \mathbb{R}^n$ randomly.

Repeat until convergence: {

For every i, set

$$c^{(i)} := \arg\min_j \| x^{(i)} - \mu_j \|^2 \tag{9}$$

For every j , set

$$\mu_j := \frac{\sum_{i=1}^{m} 1\left\{c^{(i)} = j\right\} x^{(i)}}{\sum_{i=1}^{m} 1\left\{c^{(i)} = j\right\}} \tag{10}$$

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Within cluster variation for the K-th cluster

$$\frac{1}{|C_k|}\sum_{i,i'\in C_k}\sum_{j=1}^{P}(x_{ij}-x_{i'j})^2 = 2\sum_{i\varepsilon C_k}\sum_{j=1}^{p}(x_{ij}-\bar{x}_{kj})^2 \qquad (11)$$

K-means follows Expectation-Maximization approach to solve the problem. The Expectation-step is used for assigning the data points to the closest cluster and the Maximization step is used for computing the centroid of each cluster.

While working with K-means algorithm need to take care of the following things, while working with clustering algorithms including K-Means, it is recommended to standardize the data because such algorithms use distance-based measurement to determine the similarity between data points.

Due to the iterative nature of K-Means and random initialization of centroids, K-Means may stick in a local optimum and may not converge to global optimum. That is why it is recommended to use different initializations of centroids.

Experimental Analysis

This experimental section shows the proposed algorithm outputs, this outputs to develop a system that will identify the patients with Diabetic Retinopathy. And also, either used the color image or gray level image used from the retina of the patient. These types of Iris images are called as fundus images. The different diabetic retinopathy diseases either fall between the normal or abnormal stages of the diseases. The Early-stage identification is very useful for the Ophthalmologist.

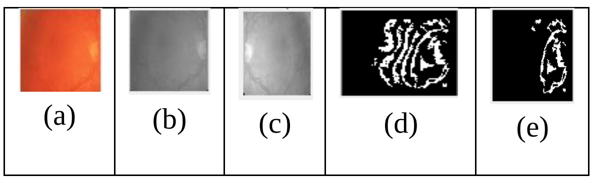

Figure 2. Diabatic Retinopathy_Image1, Gray scale image, Close and Filling Image, Filtered Image

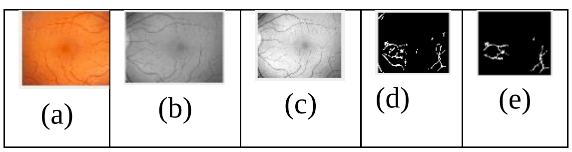

Figure 3. Diabatic Retinopathy_Image1, Gray scale image, Close, Filling Image, Filtered Image

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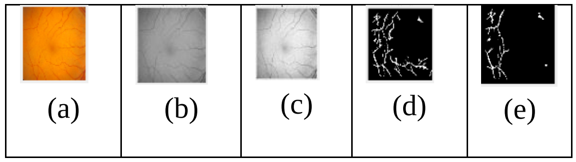

Figure 4. Diabatic Retinopathy_Image1, Gray scale image, Close, Filling Image, Filtered Image

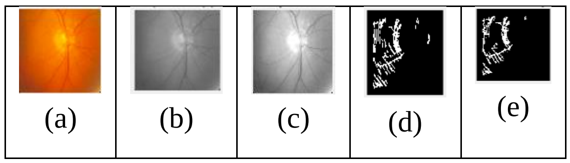

Figure 5. Diabatic Retinopathy_Image1, Gray scale image, Close and Filling Image, Filtered Image

S.NO	Classification
Diabatic Retinopathy_Image1	Normal
Diabatic Retinopathy_Image2	Normal
Diabatic Retinopathy_Image3	Diabetic Retinopathy Symptoms Detected
Diabatic Retinopathy_Image4	Normal

Table 1. Proposed algorithm classification

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	TPR (AVG)	FPR (AVG)	Accuracy (AVG)
Proposed Algorithm	0.72343	0.0211	0.92343

Table 2. Performance Evaluation results

Conclusion

Development of this algorithm will be able to identify the patients either affected Normal or Abnormal stage. The early-stage identification is very useful for the ophthalmologist in medical field. Equalization of uneven illumination of the set of provide fundus image is one of the major key successive points of this research work. The quality of the images provided and used in medical field is vey poor and very tedious for visual manual grading by the Ophthalmologists. The quality of which is firstly improved by histogram equalization. And also, diseases identification classifications stages are evaluated and implemented. These stages provide a good output result in the diagnosis process, useful for the medical field. So, the Ophthalmologist is marking the of Diabetic Retinopathy in early stage, and easily rectify the problem by the patient. Further to increase the number of counts in database system to check the diseases.

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