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A REVIEW OF AUTOMATED DIABETIC RETINOPATHY DIAGNOSIS FROM FUNDUS IMAGE

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ABSTRACT

A fundus camera provides digitised data in the form of a fundus image that can be effectively used for the computerised automated detection of diabetic retinopathy. A completely automated screening system for the disease can largely reduces the burden of the specialist and saves cost. Noise and other disturbances that occur during image acquisition may lead to false detection of the disease and this is overcome by various image processing techniques. Following this different features are extracted which serves as the guideline to identify and grade the severity of the disease. Based on the extracted features classification of the retinal image as normal or abnormal is brought about. In literature various techniques for feature extraction and different types of classifiers have been used to improve sensitivity and specificity. FROC analysis and confusion matrix are used to evaluate the system performance. In this paper critical analysis of various algorithms and classifiers is done that have been used for the automated diagnosis.

Keywords: *Diabetic Retinopathy, Fundus Image, Classifier, Sensitivity, Specificity*

1. INTRODUCTION

Diabetic retinopathy occurs in patients suffering from diabetes, which causes damage to the retina of the eye. This eventually leads to total vision loss. Diabetes is caused due to the body's inability to store and make use of the sugar level in the blood .Usually there are no early visible symptoms of the disease and as the disease progresses the presence of micro aneurysms, exudates both hard and soft and new blood vessels can be observed.

Diabetic retinopathy causes damage to the blood vessels in the retina, and this causes fluid to leak to leak into the macula region of the retina causing it to swell and leading to blurred vision. In order to improve blood circulation blood vessels form on the surface and these abnormal vessels leak and block vision. Diabetic retinopathy is of two types namely non proliferative and proliferative type. Non proliferative is the early stage of the disease characterised by the presence of micro aneurysms. As the disease progresses the retina is deprived of oxygen and new blood vessels are formed in the retina. These vessels eventually leak and leads to clouding vision.

Micro aneurysms are small red dots on the retinal surface, which occur due to capillary occlusion leading to lack of oxygen and progression of the disease. They are less than the diameter of the optic vein .Accumulation of proteins and lipids occur in the form of exudates. Vision loss occurs when they occur in the macula.

Exudates appear as yellow or white structures in the retina. There are two types of exudates based on their appearance and occurrence. Hard exudates have well defined boundaries and the soft exudates have unclear boundaries also know as cotton wool spots.

Haemorrhages in the retina occur due to bleeding. Dot haemorrhages lie deep within the retina and reflect leakage of the veins and capillaries. Dot haemorrhages are an indication of diabetic retinopathy.

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2. PRE PROCESSING

Pre processing is done to improve the image quality for the stages that follow. The image pixel values are permanently altered and the improved data is used for analysis. Pre processing suppresses undesired information and enhances required features. Pre processing involves brightness correction, edge detection, intensity adjustment, histogram equalisation and so on.

2.1 Morphological Transformation

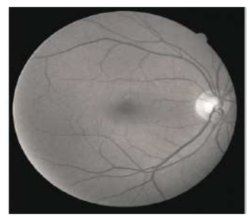
Dark lesions have very low content in the green colour plane as a result pre-processing is done in this plane [1]. Moreover the variation in background intensity of the image in the green plane is less. Hence the green channel of an image is obtained initially and for every pixel p in the image we consider a neighbourhood Ip centred around the selected pixel. The pixel is considered as darker than the surrounding if the gray level of the pixel is lesser than the fraction tG of the mean of Ip.

$P<tG.mean(Ip)$

The areas darker than the normal retina are detected .A binary image is obtained finally with non zero values for selected dark pixels.

A shade corrected image is obtained by subtracting the median filtered image from the original image [3]. The blood vessels are eliminated from the shade corrected image by a top hat transform. The vasculature present in the transformed image is removed by subtracting thee transformed image from the original image. The micro aneurysms are detected by applying matched filtering, this is done comparing a model of a micro aneurysm with each position of the image and accepting values greater than the threshold value [3] .

In the method proposed by C.I.O .Martins et al [5] the green plane of the image undergoes shade correction .The shade corrected image is top hat transformed to segment the vessels present in the image. In order to eliminate the blood vessels a vascular tree algorithm [6].The vascular tree is considered as the only part of the image that is uniform throughout. Morphological opening with a linear structuring element of size 15 pixels is used to remove rounded bright zones of size less than 15 pixels. The contrast is improved by obtaining the sum of the top hat transforms. The resulting images are noisy and Gaussian smoothing is used to eliminate the noise present in the image. To completely eliminate dark lesions a linear opening by reconstruction of size 15, a linear closing by reconstruction of size 15, linear opening of size 29 is done alternatively. The reconstructed image is subtracted from the shade corrected image; matched filter of size 11X11 pixels is then used. A threshold value is set which results in a binary image. The binary image is not a replica of the original image as a result region growing is done using the darkest pixel as the starting point.


(a)


(b)

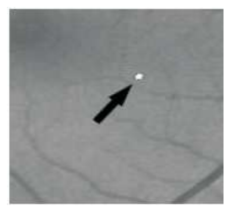

(c)

Figure 1.(a) Green plane retinal image from DRIVE database (b) Full image with micro aneurysms (c) MA detail.

Geodesic dilation is carried out on the opened image [7] and the resulting image is histogram equalised to enhance the candidate lesions. Thresholding that makes use of constant false alarm rate technique is used to separate the candidate lesions. The threshold value is made proportional to the square root of fourth order moment for accurately isolating the dark lesions.

A global contrast operator is defined for pre-processing in the method given by [8] .Filtering step is carried out to avoid darkening due to lesions. This operator was initially defined by Walter [9] and a slight variation of this operator was given by Niemeijer et al [10]. A polynomial contrast enhancement operator that assigns new gray level to each pixel is used [11] but this results in the attenuation of a dark detail situated in a dark region. To overcome this, a contrast operator is used, wherein the global mean is substituted by a

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local background approximation. This process leads to darkening of lesions near bright objects. Area opening is carried out to remove the bright objects in the image, the background is normalised by employing the method given by Foracchia et al [12].The pre-processed image is obtained by convolving with a Gaussian filter that acts as a matched filter[13] to attenuate the noise present in the image.

Akara Sopharak et al [20] in their work to detect exudates made use of morphological filtering. The pre-processing here involves the conversion of image in RGB space to HSI colour space [21], as the intensity components are removed from the remaining colour components. Median filtering is done to reduce the effect of noise. Contrast adaptive histogram equalisation is applied to small regions of the image. The small regions are combined by bilinear interpolation after equalisation. Exudates are regions of high intensity values.

2.2 Median Filtering

A series of image processing techniques were used in the method proposed by Atushi Mizutani et al [2] which includes brightness correction, gamma correction and contrast enhancement. The micro aneurysms have high contrast in the green plane therefore the green plane of the image is obtained. The width of smaller images are unified with the larger images present in the database by bicubic convolution method. Median filtering is employed to reduce the effect of noise.

The green plane image is shade corrected image is applied using a 56x56 median filter [14]. A top hat transform is applied using a 25 pixel long linear structuring element which is spaced 180 degrees apart. Two matched filters are used to approximate the characteristics of the objects of different sizes and each are thresholded and are combined. The result is a micro aneurysm seed image. The region growing process is carried out using the seed pixel .From the region grown eighty features are extracted.

Hussain F.Jaafar et al used pure splitting method to detect exudates from retinal images. A top hat transform is applied to the image and is median filtered. The optic disc is detected and removed. An adaptive local thresholding method is used. The image is divided into sub images and local thresholding is applied to each sub image, followed by global thresholding to each sub image. Region based segmentation is applied which includes pure splitting, merging and split and merge methods. Each region is tested for homogeneity based on the features. The boundary of the candidates are outlined based on the local variation of the image pixels.

Akara Sopharak et al [28] in their work proposed a method for detection of diabetic retinopathy by detecting the presence of exudates in the retinal image. The pre-processing consists of conversion of RGB to gray scale and median filtering is carried out to remove noise. Histogram equalisation is the next step that follows. Exudates and optic disc has the highest intensity values in the pre-processed image. The optic disc is eliminated based on the texture, as the optic disc has a smooth texture. Based on entropy the texture is analysed, low entropy is an indication that the region smooth. Otsu's binarisation algorithm is used to remove complex regions in the image. The binarised image has many components of which the largest connected component is selected and circularity is found .Dilation is applied to the result. The pre-processing stage in the work proposed by Bernhard M.Ege et al[23] consists of filtering the input image initially with a mean filter. A background estimation is made using a large median filter and most of the abnormalities are removed from the image .The objects coming out of the pre-processing stage consists of the possible abnormalities. The shape of the abnormalities is estimated using a region growing algorithm.

2.3 Radon Cliff Operator

Luca Giancardo et al [15] presented his work on the detection of micro aneurysms with the help of Radon Cliff operator. The pre-processing involves the analysis of discrete stationary wavelets is performed in the green plane of the image. A signed image is obtained by reconstructing the image by replacing first scale plane with zeros; the background is removed by undergoing this process. The negative pixels are then extracted and normalised. By the following operations the optic nerve, bright lesions are eliminated enhancing the micro aneurysms and vessels. The radon cliff operator is applied to the gray scale image and for pixel values greater than 215 are considered as candidates.

2.4 Thresholding

[19] S.Kavitha et al proposed a method for detection of hard and soft exudates wherein the pre-processing involves colour space conversion into lab colour space and detection of fundus region

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[20]. The Lab colour space image is then converted into binary image by thresholding. Then the binary image is morphologically closed. Then a fundus mask is created with pixels at the fundus marked as 1 and pixels in the background marked as 0.

Yuji Hatanaka et al used brightness correction to improve the automatic detection of haemorrhages in fundus images. The image is normalised and gamma corrected .The optic nerve head is detected and removed by p-tile method[10 hae detc].The retinal image is smoothened using two kernels and the difference between the smoothened images is found out and the result is segmented by thresholding. The vessel ends are not detected, a 9 x9 mask is used for smoothing. The result is thresholded but the candidates on the vessels are not clearly detected and the false positives are eliminated by using a length width ratio.

2.5 Histogram Equalisation And Specification

Gerald Schaefer et al [29] utilised neural network, the pre processing stage histogram equalisation and specialisation. A sliding window technique is used the regions covered by the window serve as the input features. The pre-processing is not done in the green plane, the full colour data is considered. A 9x9 sized window is used, if the exudates is the center pixel then it is considered as positive sample else it is considered as negative sample. A target vector is created and based on the positive and negative samples and the vector is set as 0 or 1.

3. MICRO ANEURYSMS

3.1 Density Function

The spatial relationship of the pixels has to be considered in the next step to differentiate between the candidate lesions, noise and pigment variability. A density function [1] is defined to find the number of similar pixels in the neighbourhood of the selected pixel. A threshold value is set to eliminate pixels belonging to the optic disk and the blood vessels and as a result the dark lesions are identified.

3.2 Double Ring Filter

A double ring filter with inner and outer ring diameters of 5 and 13 pixels [2] is used for detecting micro aneurysms in the surrounding retinal regions of the image. The candidate lesion is a micro aneurysm if the value of pixel in the inner circle of the double ring filter is lower than the pixel in outer ring. A maximum of 300 micro aneurysms were considered as candidate lesions in each image. In order to reduce the number of false positives due to blood vessel a double ring filter of diameter 7 and 21 pixels which corresponds to the inner and outer diameter is used. Lesions occurring on the blood vessels are considered as false positives and are eliminated. The shapes of the candidate lesions are examined to reduce the number of false positives.

Features such as area, perimeter, circularity, intensity and mean intensity are extracted.[5].

3.3 Region Growing

Region growing algorithm to find the morphology of the candidate. Eight features are defined to further improve the accuracy of detection in the method given by Spencer et al [4].Four intensity measures which are similar to those given by Spencer et al but with a modification in that the measures were multiplied with a scale factor for better discrimination between micro aneurysms and other parts of the vasculature .Thus a rule based classifier is defined.

Region growing is used to group similar pixels into the target lesions namely micro aneurysms [6].The pixel with lowest intensity is used as the seed pixel and the procedure stops when the condition of region growing is not satisfied, the procedure continues by selecting a new seed pixel. The features extracted include circularity, area ,aspect ratio and colour feature are extracted.

Bob Zhang et al [9] in their work proposed a method for candidate detection with multi-scale Gaussian correlation filtering and region growing. As MA has Gaussian characteristics they can be detected using a Gaussian function. The correlation coefficient provides the resemblance between the MA and the Gaussian function and thus paves way for their detection.

3.4 Morphological Filtering

Morphological closing leads to tortuous vessel like patterns being treated as MA, an ideal operator with all structuring elements having large diameter is used [7].This method was proposed initially by Walter et al[16] and Vincent at al[17] and was modified later by Breen and Jones[18].15 features which include the binary features ,gray level and colour features are extracted.

Lee Streeter et al[14] in his work extracted some eight features for the detection of micro aneurysms which include mean , standard deviation ,moment

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,RGB and HSV colour spaces ,mean and standard deviation ,area and aspect ratio. This forms the dataset to train the classifier. All objects that have features outside the feature space of true MA are removed from the data set. Linear discriminant analysis is used for the classification.

(a) (b)

Figure 2. (a)A colour retinal image with seven micro aneurysms identified by the ophthalmologist (b) Six micro aneurysms detected by the algorithm with no false positives highlighted in white.

4. EXUDATES

4.1 Non Linear Diffusion Segmentation

Non linear diffusion segmentation is used to segment out the exudates [19] and is based on the non linear diffusion segmentation given by Perona and Malik.This is given by,

The likelihood can be calculated by$| \nabla u |^2$

$$\partial_t (u)=div\ (g(| \nabla u |^2 \nabla u\ ) \quad (1)$$

The amount of smoothing can be modulated at each location by the present magnitude of the gradient ,

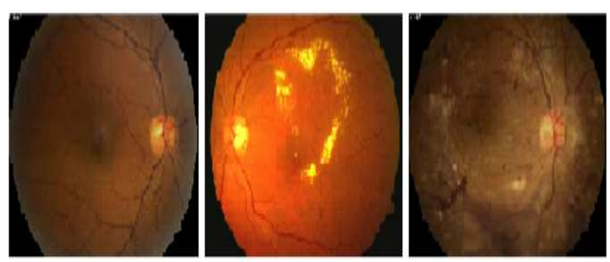
$$g(s^2)=1/(1+ (s^2/\lambda^2) \quad (\lambda>0) \quad (2)$$

Non linear diffusion segmentation is done to indentify pixels within a region to determine the location of boundary. For the detection of exudates the entire image is divided into non overlapping blocks and for each block the histogram is obtained. Based on the characteristics of the histogram the hard and soft exudates are detected.

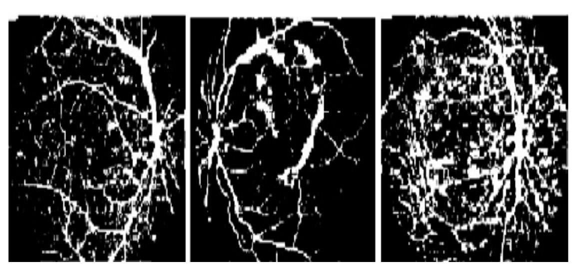
4.2 Fuzzy C-Means Clustering

Fuzzy C-means clustering is used to detect exudates based on four features and eight clusters are formed for 40 retinal images [22].The original image with the exudates region absent is then subtracted from the original image to find the areas where exudates are present. The cluster image is used as marker and original image as mask and morphological reconstruction by dilation is carried out. Then thresholding is applied and difference between the original and reconstructed image is found and the result is superimposed on the original retinal image.

Akara Sopharak et al used fuzzy C-means clustering for the detection of exudates in retina images. In the pre-processing stage the image the exudates are distinguished by means of the intensity level .the image is converted from the RGB colour space to HSI colour space and median filtering is applied to the I plane of the image and a contrast enhanced adaptive histogram equalisation is applied[22]. The standard deviation of the contrast enhanced image is used as one of the features for detecting the exudates. The hue of the HSI image is the next feature to be extracted. The number of edge pixels is the final feature for clustering. A sobel edge detector is used [30]. The edge pixels contain blood vessels as a result decorrelation stretching is applied to enhance the colour features and distinguish them, thresholding is applied to detect the blood vessels. As soft exudates are present without strong edges, pixels with high value in the decorrelation image are chosen and added to the previous image. Next the optic disc is removed by using an entropy feature. As optic disc has low intensity in the intensity image it is removed by thresholding, moreover the optic disc has the largest area among the objects present in the image .To ensure the neighbouring pixels are included in a dilation is carried out using a disc structuring element .Then the number of white pixels in the image are found.



(a)



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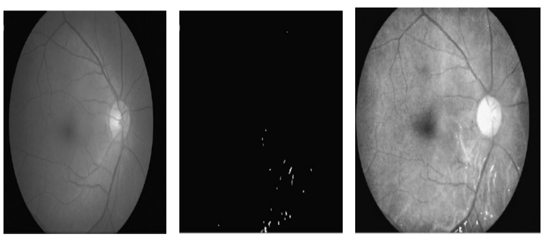
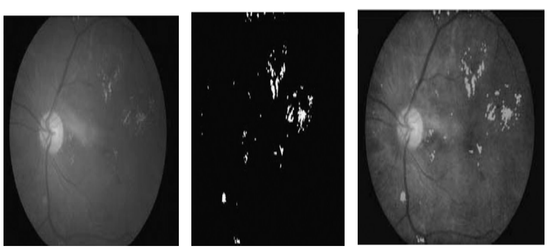
(b)

(c)

Figure 3 (a) Pre-processing of the retinal image (b) segmentation (c) detection of exudates



(a) (b) (c)



(d) (e) (f)

Figure 4. (a) Original retinal image (b) detected exudates like structures (c) detected structures superimposed on retinal image (d) diseased retinal image (e) detected exudates like structures (f) detected structures superimposed on retinal image.

Wei Lin et al [31] in their work for the detection of exudates eliminated the optic disc initially by means of a fuzzy convergence algorithm [32].The exudates region are estimated by computing the average colour pixel value around the optic disc, this may include the optic disc region. The optic disc region is eliminated again using the above algorithm [33]. This is followed by morphological opening to fill gaps in the exudates region.

Giri Babu Kande et al [34] employed fuzzy C means clustering to isolate regions where exudates are present [35]. Here pixels having same gray level are grouped together followed by grouping of connected pixel regions. As FCM is time consuming as it is an iterative algorithm the histogram is applied as the input to the algorithm [36].

4.3 NEURAL NETWORK SYSTEM

Gerald Schaefer et al [29] employed neural networks for the detection of exudates. The pre processing is done in the entire colour plane unlike other methods that consider only the green plane and then applying histogram equalisation to remove the non uniform lighting conditions. A sliding window mask is moved over the entire pixel region such that each pixel falls in the center of the mask [51]. Pixels belonging to the exudates region are considered as positive sample to the training set and all other regions are considered as negative samples. Based on the positive or negative sample indicated as 0 or 1 a target vector is created for the neural network system. This is followed by the application of principal component analysis for the detection of exudates.

4.4 CONTEXTUAL CLUSTERING

Contextual clustering put forward by [26] for detecting MR lesions is used here [25].The contextual information is used to enhance the detection rate of exudates. Fuzzy art neural network [27] is also used for the detection of exudates. From the contrast enhanced image features such as convex area, solidity and orientation are extracted. The optic disc is eliminated based on the fact that it is the object with the largest diameter in the image. Classification is based on four features namely convex area, convex image.

4.5 Morphological Filtering

Morphological dilation at two different scales are carried out followed by subtraction of the obtained results [40]. Morphological filling is carried out to isolate the exudates regions. A linear classifier is constructed based on the colour features and edge properties of the exudates [41]. Patches that satisfy both the brightness and edge properties are classified as exudates.

4.6 Pure Splitting

Hussain. F et al [42] in their work for the detection of exudates employed shade correction technique and optic disc elimination [43].This is followed by a pure splitting technique and

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histogram based thresholding , local variations of the pixels are calculated based on coarse segmentation [44].

Following pure splitting the sub images are histogram thresholded by running a global threshold value throughout the image with varying threshold value α and is given as,

$$G_1 = \sum_{l \in k} T_{\alpha_l} P_l \tag{3}$$

Exudates have clear boundaries compared to the other retinal features which can serve to grade the severity of the disease.The standard deviation of the image is found out as a result, a local variation operator is applied and prior to this the blood vessels has to be eliminated. This is done by a closing operation ψ to the pre-processed image (Gp) with disk structuring element ζ of radius 6.The image obtained as a result is given as G2,

$$G_2 = \psi^{\zeta_1} G_p \tag{4}$$

Local operator is applied and the resulting image is given by,

$$G_3(x) = \frac{1}{N+1} \sum_{i \in w(x)} G_2(i) - \mu(x) \tag{5}$$

Coarse segmentation of exudates are done using morphological clear operator given by,

$$G_4 = C(D^{\zeta_2}[T_\alpha(G_3(x))] \tag{6}$$

Exudates are finally detected by combining results of both adaptive thresholding and coarse segmentation.

4.7 K Means Clustering

K means clustering [45] is used to detect exudates and non exudates and as a result the number of clusters formed is two. Exudates are located in high intensity range whereas the other lesions are present in the low intensity range. Maximum and minimum intensity values are calculated and serve as a distance measure, the process is repeated and the cluster centers are updated in each step.

4.8 Mixture Models

Mixture models threshold the image to detect the exudates [46]. K means clustering algorithm is used initialise the parameters of the algorithm. Once the mixture model parameters converge, the third Gaussian component is associated with the exudates region [47]. Following the thresholding operation principal component analysis is used to eliminate the optic disc from the region detected followed by edge strength measurement to isolate the cotton wool spots from the hard exudates region [48]. The two threshold values are used to finally detect the hard exudates.

4.9 Watershed Transformation

Thomas Walter et al in their work detected exudates based on their high gray level variation and morphological reconstruction is used to detect the contours. Morphological filtering is used to eliminate the optic disc region and water shed transformation. The exudates are detected based on high gray level and contrast.

4.10 Linear Discriminant Analysis

Clara I.Sanchez et al developed a method for the detection of hard exudates based on Fisher's linear discriminant analysis. Meindert Niemeijer et al [24] in their work on the automatic detection of diabetic retinopathy proposed a method for the early detection of exudates, cotton wool spots and drusens.

4.11 Level Set Method

W.Sae-Tang et al detected exudates by non uniform illumination background subtraction. Initially the image background with non uniform illumination is estimated. Background estimation is carried out. A weighted colour fundus image is obtained. The colour image is converted into a gray scale image , average filter is used to obtain the smoothened image. The upper bound is found by adding a constant to the smooth image that is obtained and lower bound is got by subtracting a constant from the smoothened image and the value is 20 and 15 respectively. The unwanted data in the diagonal matrix is set to zero and the background of the image is estimated using a weighted surface fitting. To detect the exudates the background image from the gray scale image. On the dark regions of the image blood vessels and lesions are suppressed. The optic disc is then detected and eliminated. The exudates are removed by level set method.

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5.HAEMORRHAGES

5.1 Rule Based Method

A rule based method using 45 features are used to detect the haemorrhages.12 features based on concurrence matrix, 2 based on gray level difference and one based on extrema method. The false positives are eliminated using Mahalanobis distances.

5.2 Otsu Algorithm

Optic disc elimination is done by first eliminating the vessels in the optic disc by a closing operation a disc shaped structuring element is used [20]. Then the resulting image is thresholded as is used as mask to remove the optic disc, this is the marker image. The image is reconstructed by dilation is used as the mask .The difference between the reconstructed and original image was thresholded at a particular grey level. The value of a2 is different from image to image based on Otsu algorithm.

6. CLASSIFIER

6.1 K-Nearest Neighbour

The classification task consists in deriving a general classification rule for unknown candidates from this training set. There exist many methods to solve this kind of problems ; to the detection of MA, the k-nearest - neighbour (KNN) method , support vector machines , linear discriminant analysis, rule based analysis and neural network have been used. The choice of an appropriate method has two important aspects: first, the method should be robust against outliers in the training set, because it is very difficult to obtain an absolutely reliable ground truth. Second, the distribution of the features is unknown. These considerations have lead several authors to the use of KNN classifiers, which consist in assigning to a new candidate z the class to which the majority among the K nearest neighbours of z belongs. The advantages of this method are that for K reasonably large, the method becomes robust against outliers and that it is non-parametric (i.e. no assumption about the feature distribution must be made).One drawback of the method is that all neighbours have the same weight for the decision, independently of their distance from the candidate to classify. Moreover, the method might not work properly if the training set is very asymmetric for the two classes (i.e. if the sample number of one class is much larger than the sample number from the other class), particularly for large K. In order to overcome these problems and to meet the requirements discussed above, we have chosen the kernel method for density estimation, combined with Bayesian risk minimization. A post processing step is included to exclude the lesions present on the vessel.

6.2 Neural Network

The accuracy of the algorithm in detecting the candidate lesions is further improved by considering 12 features [2] which include circularity,length to width ratio ,mean value of candidate lesion ,difference between maximum and minimum pixel in the red, green and blue bits ,contrast difference between the mean value of the lesion and its surrounding .An ANN classifier is used to discriminate between the candidate and the false positive based on the 12 features. The classification utility of each feature was analysed and number of features are reduced based on the utility.

A neural network classifier with multilayer perceptron with log-Sigmoid transfer function in the output layer and linear function in the output layer which makes use of back propagation algorithm[3] using Levenberg-Marquardt a nonlinear optimization technique is used to estimate the classification performance of the feature data set.

Neural network with three layer perceptron architecture, with a single input, hidden and output layer is used [29]. The input consists of 243 neurons, 50 hidden neurons and output consists of a single neuron. A scaled conjugate gradient method was used .A network output in the range of 0-1 is obtained when the neural network classifier is used.

Three different classifiers namely Bayes, Mahalanobois distance classifier and KNN classifier are used to differentiate between the abnormalities [23]. The Mahalanbois classifier had the best results were the 69 %, 83%, 99% and 80% were the sensitivity for detection of micro aneurysms, haemorrhages, exudates and cotton wool spots..

S A Barman et al utilised neural networks and tracking algorithms to detect haemorrhages in retinal images. A multi perceptron back propagation based neural network is used here. A matched filter technique is applied to the extracted region ,the maximum value in the magnitude image is given by a black dot. Thus the haemorrhages are detected.

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Exu ref 1 C.Jayakumari et al [25] in their work of detecting exudates used contextual clustering and fuzzy art neural networks. The pre-processing stage involves the conversion of the original image into green plane image followed by normalisation to enhance the regions where exudates are present.

6.3 Sparse Representation

Sparse representation based classification [14] used in face recognition is used to classify the target MA lesions. Here the test sample is considered as a linear combination of training samples and the representation samples are as sparse as possible. If the sample from the test set belongs to the class p then the representation coefficients over all training samples only those belonging to class p will be significant while others are small and class label of the sample are determined.

6.4 Support Vector Machine

Linear discriminant analysis was used as an effective method of classification [15], and all methods that provided better results were taken into consideration and it was found that ADTree-a tree based classifier ,SVM classifier and Logistic Regression .And the performance is analysed by the help of FROC analysis.

15 features are extracted from 115,867 positive and negative samples of exudates pixels Classification is made using the Bayes classifier by repeatedly removing features till the performance of classifier does not improve.SVM classifier is trained using the features found suitable for the Bays classifier and previously removed features are added. For each pair of parameters tolerance and radial basis function is determined. These two classifiers perform better than NN classifier. The sensitivity, specificity, precision and accuracy are 92.8%, 98.52%, 53.05%, 98.41% respectively.

6.5 Histogram Based Classification

The soft and hard exudates are detected from the histogram of the overlapping blocks. A threshold value is set to detect the hard and soft exudates [20].The region of the histogram lying between 0.8 and 0.85 is considered as the region of soft exudates and the remaining regions are regions of hard exudates.

6.6 Correlation Based Method

31 features are extracted and SEPCOR [21] is used to select the most significant features used for the classification. The variability feature is used to find the separation between classes. And is given by

$$V=s(u,i)/ u(s,i) \qquad (7)$$

Where s(u,i)is the standard deviation and u(s,i) is the mean. Corelation between the features is used to eliminate the features that are correlated. Two parameters are defined for this namely the lowest V value and the highest value of V which is 0.2 and 0.8 in this particular method. The classification is spilt for dark and bright objects in the image .For dark abnormalities six feature as are defined and nine for the bright features.

6.7 Gaussian Filter

15 features are extracted from the image for the classification of exudates [28] namely the pixel intensity, standard deviation, hue, number of edge pixels, average intensity of pixel's cluster, size of cluster, average intensity of pixels in the neighbourhood of pixels, distance between pixel cluster and optic disc, filter response of 6 difference of Gaussian filters. Bayes and SVM classifier are used for the classification.

7. RESULTS

94% of the lesions present in the image were detected using this algorithm [1].The performance can be further improved by integrating this algorithm with a classifier. This makes the above algorithm less sensitive to the tradeoff between setting the threshold to be small enough in detecting small lesions and big enough to detect large haemorrhages.

The performance of the system was evaluated using FROC curves. The result was considered as a true positive detection [2] if the barycentre of the candidate is within a certain distance from the standard location of the micro aneurysm. The sensitivity of the system was 67% for 27 false positives per image.

ROC curve was obtained in [3] by varying the classifier rules of the rule based classifier. The ROC curves are near optimal because the continuous variation of rules of the classifier leads to discrete points. The algorithm achieved a sensitivity of 82% with 2.0 false positive per image for the training set and a sensitivity of 82% with 5.7 false positives per image(fppi) for the testing set. Varying the operating point resulted in sensitivity of 77% for 2.9 fppi .The FROC curves were also plotted to evaluate the performance of the system.

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ROC analysis display true and false positive and negative totals and sensitivity and specificity for cut off between 0 and 1 for a MLP neural network [5].The accuracy obtained is 84 % for this algorithm.

FROC curves were plotted to analyse the performance of the system and a comparison was made for three different classifiers namely kernel, Gaussian and knn classifiers[7] and it was observed that the three methods yielded similar results with sensitivity of 67 % for 1.4 fppi .Bayesian classifier gives a sensitivity of 94 % and outperforms other classifiers using the same algorithm.

The detector output at test point was compared using FROC analysis and the area under the curve (AUC) the effect of changing various parameters are observed[14].

FROC analysis is used to investigate and compare classifiers, a lower area limit [15] classifies objects as being micro aneurysms. The classification and testing of datasets are done LDA and two FROC curves for each area limit. Objects below the lower area limit are considered as non micro aneurysms, these may also contain true micro aneurysms as they are not detected in the pre processing stage, the sensitivity is corrected according to the efficiency of the detection algorithm. Sensitivity of 56% at 5.7 fppi was achieved, this false positive rate is too high ,but in the case of diabetic retinopathy detection the presence of micro aneurysm is an early indication of the disease. So the detection of at least one micro aneurysms per image without any false detection is the main criteria to determine the efficiency of the algorithm.

The detection of micro aneurysms using Radon cliff operator [16] achieved a sensitivity of 41% and 25% for a single false positive per image. The radon cliff operator has various advantages as no explicit training is required for pattern recognition and can be used for detection of micro aneurysms of different sizes .This also distinguishes between micro aneurysms and retinal vessels.

The performance of the fuzzy C means clustering algorithm is analyse [22] and the sensitivity ,specificity ,PPV,PLR and accuracy were examined.FCM clustering produced high true positive and at the same time high false positive whereas the PPV and PLR values were found to be low.

A ROC analysis is carried out to evaluate the performance of the algorithm [29].The area under the curve analysis is also carried out and it yields a value of 1 for identifying the true and false exudates and 0.5 for random guessing cases. The sensitivity and specificity was found to be 94.78 and 94.29 respectively.

A clinician reference standard images with exudates have 91.2, 99.3 and 99.5 % sensitivity, specificity and accuracy respectively in the algorithm proposed by Hussain F.Jaafar et al .

8. LIMITATION IN THE CURRENT APPROACHES

A common approach to the detection of diabetic retinopathy from retinal image involves the identification of retinal features such as the optic disc, blood vessels and fovea and then localizing the necessary structures such as micro aneurysms and exudates for the detection .The localization of similarly coloured retinal structures is challenging.

As discussed in the previous section it has been noted that the existing methods have variations in the performance of classifiers. Each algorithm yields different values of accuracy, specificity and sensitivity that solely determine the accurate detection of the disease. As a result each algorithm aims at improving its classification rate compared to the previously existing methods. These automated detection methods are limited by the amount of data that is made available and the variety of methods that can be used to solve the problem. As the methods involved in the detection are complex the running time in normal computers is high.

9. IDENTIFICAITON OF OPEN REASEARCH ISSUES

Mass screening of retinal images of patients for the presence of diabetic retinopathy can effectively reduce the possibility of blindness in affected patients. Such screening systems mainly benefit patients from rural areas who are actually unaware about the presence of the disease. Due to the limitation of medical facilities and the number of ophthalmologists the data regarding the screening can be transmitted via satellite links to the ophthalmologists at the hospital and the result can be communicated via these links. This can be further enhanced by the use of Wifi long distance networks which provides video conferencing facility between the patients at the rural camp and the doctors at the hospital.

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In order to support the complex operations involved in the automated detection imaging computers backed up by high performance embedded systems can be used. These systems can be interfaced with an ophthalmoscope from which the retinal image is inputted and a separate display device can be used to display the result regarding the presence or absence of the disease. Further the algorithms can be enhanced to produce results regarding the grade and severity of the disease.

10 . CONCLUSION

This work depicts the various stages involved in the diagnosis of diabetic retinopathy from fundus image. Comparison of various steps in pre-processing is done, to overcome the problem of contrast, incorrect illumination and noise using various methods. Various algorithms have been compared for the extractions of features micro aneurysms, haemorrhages, exudates from fundus image. Different types of classifier and its performance are analysed for the automated diagnosis of diabetic retinopathy from the features extracted. Performance analysis of various classifiers is done in terms of sensitivity, specificity, confusion matrix and FROC analysis.

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