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Detection and Classification of Early Stage Lesions in Diabetic Retinopathy using Color Fundus Images

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Abstract- Detection of lesions and classification of Diabetic Retinopathy (DR) play an important role in day-to-day life. In this proposed system, colour fundus image is pre-processed using morphological operations to recover from noises and it is converted into HSV colorspace. Fuzzy C-Means Clustering algorithm (FCMC) is used for segmenting the early stage lesions such as Microaneurysms (Ma), Haemorrhages (HE) and Exudates. Hybrid features such as colour correlogram and speeded up robust features (surf) are extracted to train the classifier. Cascaded Rotation Forest (CRF) classifier is used for classification of diabetic retinopathy. The proposed system increases the accuracy of detection and it has got high sensitivity.

Keywords- Diabetic Retinopathy (DR); Microaneurysms (Ma); Haemorrhages (HE); Exudates; morphological operations; Fuzzy C-Means Clustering algorithm (FCMC);Cascaded Rotation Forest (CRF) classifier.

I. INTRODUCTION

Presently, many people are affected by diabetes. It occurs when blood sugar increases. Lack of insulin will cause glucose to stay into our blood and this will increase blood sugar. Over time, it will cause serious health issues. One of the problems is diabetic retinopathy. Diabetic retinopathy is the disease that can affect both of the eyes. This is damage to the blood vessels in the retina. High blood sugar sparks off swelling and blockage of the blood vessels. Eventually, blood supply to the retina will be suspended. Consequently, new blood vessels will grow in our eyes but these new blood vessels are narrow and they can leak blood. This blood leakage will affect our vision and lead to blindness. The symptoms include dim or oscillate vision, dark or black vision or complete vision loss.

In the early stage of diabetic retinopathy, Microaneurysms which is swelling that appears in the wall of the retinal blood vessels and this inflammation interrupts and discharge tiny blood dots. Over time, its fracture introduces haemorrhages and exudates are yellow–white cellular lipids which can be discharged from retinal capillaries. It may vary from speckle to patches or even form like circular rings. In the advanced stage, blood vessels disconnect causing new blood vessels to grow largely and that can also leak blood which rise to detachment of retina from back of the eye. Subsequently, nerves which carries signal from eye to brain will be damaged resulting in glaucoma.

To exterminate the root of DR, monitoring and maintaining of blood sugar, blood pressure and cholesterol is necessary. Regular exercising and eye screening will help to get rid of diabetic retinopathy. Generally, clinical check-up will consume more time but self testing and diagnosis is less cost and less time consuming. An automatic detection of early signs of DR will allow the patients to go for eye-screening at home. This proposed system not only focuses microaneurysms but also haemorrhages and exudates and so it may be considered as the common algorithm for finding all of the early stage lesions in diabetic retinopathy.

II. RELATED WORKS

In this work [1] an algorithm is proposed to detect diabetic retinopathy based on human visual system sensitive to direction, colour and brightness. The achieved AUC is 0.9 which is superior to the other methods. In [2] author proposed algorithm for the detection & classification of diabetic retinopathy into normal, NPDR & PDR. Image is resized and converted into gray scale. Adaptive histogram equalisation redistributes the intensity values and DWT is used to extract frequency information. Matched filter is used to reduce noise. For the detection of blood vessels fuzzy C means clustering is preferred. Data from the blood vessels is used to grade the severity of the disease. SVM & PNN classifier is used for the classification of the disease. Sensitivity and specificity are 72% and 71% respectively. Mask detection and score computational system is used [3] for the detection of exudates in retinal fundus images.

Image is pre-processed using contrast limited adaptive histogram equalization [4]and median filtering and retinal blood vessel is extracted by mean-C thresholding segmentation and post processing uses morphological closing operation to eliminate separated pixels. Accuracy is achieved as 0.955.

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In this proposed work, fundus image is pre-processed [5] and morphological operations are done to extract the features. The features such as GLCM and Splat are extracted to train the classifier. The achieved value of sensitivity and specificity is 87% and 100% respectively and the accuracy is 86%. SVM and KNN classifier is used for classification.

In [6] proposed algorithm uses multilayer perceptron neural network classifier for detecting diabetic retinopathy in fundus images. It includes pre-processing such as decolouring and resizing. No segmentation technique is introduced into this system. After the pre-processing stage, feature extraction is done. Features are 64-point DCT features and 9 statistical features and optimised feature vector is formed for training and testing the MLPNN classifier. Train N times method of training is used for training the classifier. There are 11 hidden elements and transfer function is tanh. The proposed system achieved high accuracy of 100% in both of the training and testing stages.

This proposed framework [7] consists of two approaches: semi-automated and automated for the detection of microaneurysms and Hemorrhages. In the semi automated approach, SHCS (semi automated hessian-based candidate selection algorithm) and thresholding is used to detect the lesions of Diabetic Retinopathy. In the automated approach, AHCS (automated hessian-based candidate selection algorithm) and feature extraction is employed and the extracted features are used to train the SVM classifier. The results showed that semi automated approach detection rate is found to be lesser than that of the automated approach. The proposed system help diagnose the detection [8] and severity of DR by extracting important features from fundus images using image processing. Based on the area measured from pre-processing and feature extraction, severity of the disease is calculated. From the level of severity, the author categorised the DR into mild, moderate and severe stages.

The author has surveyed [9] all current image processing based techniques for the detection of diabetic retinopathy. In [10] there are three stages to detect and classify diabetic retinopathy. In the first step, canny edge detection and histogram equalisation is performed. In the second stage, principal component analysis is used for image reduction and extraction of features is done. In the third stage, different classifiers such as are used for classification of DR into proliferative and non-proliferative DR. The results show that KNN F-measure is 68.7% which is better than the other classifiers for the dataset consists of 151 different resolution images.

III .PROPOSED METHODOLOGY

The block diagram of detection and classification of early stage lesions in Diabetic Retinopathy using colour fundus images is shown in Fig.1.The colour fundus image consist of three channels: Red, green and blue. The Principal Component Analysis (PCA) algorithm is applied to input fundus image for data reduction .It is followed by data transformation. The three channels are separated and then morphological technique (opening-by-reconstruction) is applied for three channels to wipe out the image. Subsequently, all three channels are concatenated. RGB colour image is converted to HSV colorspace. Fuzzy C-Means Clustering algorithm is applied for segmenting the early stage lesions in diabetic retinopathy and output is converted to RGB format. Hybrid features such as colour correlogram is extracted from HSV colorspace output and speeded up robust features (surf) are extracted from the segmented RGB image. It forms the feature vector and it is used to train Cascaded Rotation Forest (CRF) classifier for classification of early stage lesions.

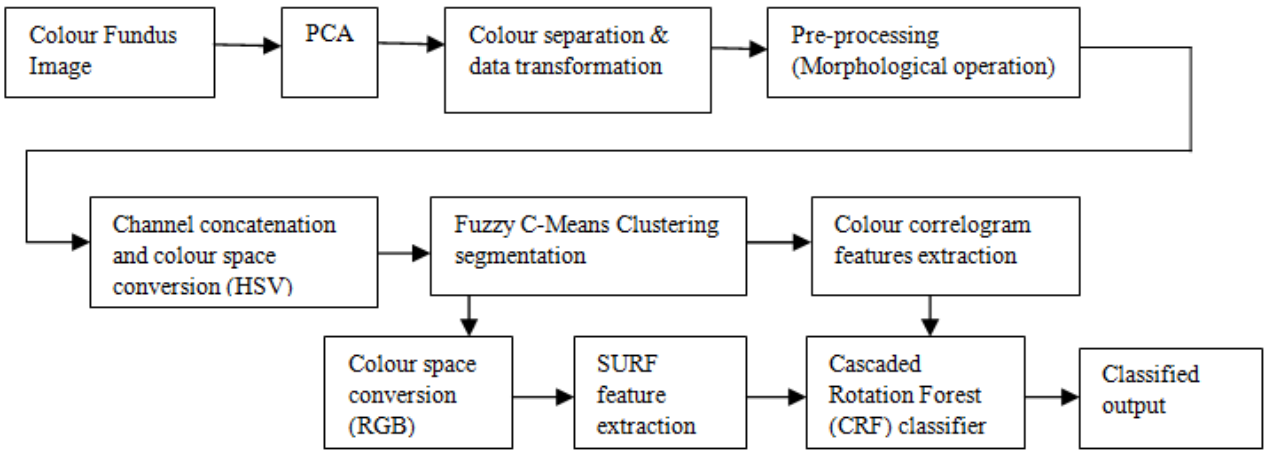

Fig. 1. Block diagram of proposed method

A. Pre-processing

Image is acquired from fundus camera and the input data is a 3D data consists of three channels (RGB): Red, Green and Blue. The Principal Component Analysis (PCA) algorithm is applied to colour fundus image for data reduction and to keep most significant Eigen vectors and subsequently, data transformation is applied. For further processing, input image must be free from noises and low illumination. Morphological operation such as opening-by-reconstruction is used to remove small unwanted parts. Opening by reconstruction of an image I using structuring element S is defined as RI (I ⊖ S).

The input fundus image and morphological reconstructed image is shown in Fig. 2 & Fig. 3 respectively. To be more robustness, RGB image is converted to Hue Saturation Value (HSV) colour space. Since there are many advantages like separating colour and intensity information, fast processing, shadow
removing & easy human perception we preferred HSV colour space. The formula for calculating HSV is given below:

$$H = \begin{cases} 0^\circ & \alpha = 0 \\ 60^\circ * ((G1 - B1/\alpha)\ mod\ 6) & , C = R1 \\ 60^\circ * ((B1 - R1/\alpha) + 2) & , C = G1 \\ 60^\circ * ((R1 - G1/\alpha) + 4) & , C = B1 \end{cases} \quad -- (1)$$

$$S = \begin{cases} 0 & , C = 0 \\ \alpha/C & , C \neq 0 \end{cases} \quad -- \quad (2)$$

$$V = C \quad -- \quad (3)$$

Where R1=R/255 ,G1=G/255 , B1=B/255 ,
C =Max(R1 ,G1 , B1) , C_{min} =Min(R1 ,G1 , B1) &
α = C - C_{min} .The HSV colour space converted pre-processed fundus input image is shown in Fig 4..

Fig 2.Input fundus image

Fig.3.Morphological reconstructed image

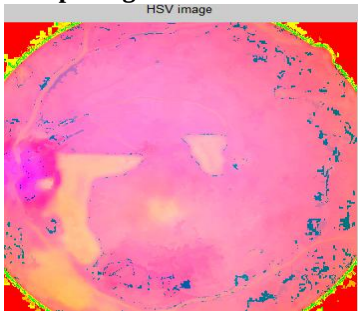

Fig. 4.HSV image

B. Segmentation

The Fuzzy C-Means Clustering algorithm (FCMC) is an iterative process that explores fuzzy clusters set and the linked cluster centres. It segregates the image pixels into different clusters based on the degree of relationship. The degree of relationship is more within the cluster and it is less between the clusters. Fuzzy partitioning allows one image pixel to be connected to more than one cluster with different membership grade. This feature makes FCMC algorithm as an important supportive tool for computer aided medical diagnosis system and the sensitivity can be increased. Each cluster is linked with a membership function and it conveys the amount to which image pixels associate to each cluster. The algorithm steps are given below:

1. Initialising the number of clusters.
2. Selecting cluster centres randomly.
3. Determining Fuzzy membership grade.
4. Computing fuzzy centres.
5. Repeat steps 3 & 4 until the minimum value of objective function is achieved. Sum of squared error (objective function) Jp (U,V) for the fuzzy clusters set is given by

$$J_p(U,V) = \sum_{k=1}^{n} \sum_{j=1}^{c} (U_{jk})^p \ \|I_k - v_j\|^2 \quad -- (4)$$

$1 \leq p \leq \infty$, c - Number of clusters, n –Number of pixels, U – membership matrix, V- set of cluster centres, I-input image, v- cluster centre. $\|I_k - v_j\|^2$ is the similarity measure and indicate the distance between the image pixels I_k and the cluster centre v_j.The output from FCMC is shown in Fig. 5 and the result shows that DR lesions form one cluster and the unaffected area form another cluster.

Fig. 5.FCMC output

C. Feature Extraction

Colour correlogram & speeded up robust features (surf) features are extracted. Colour correlogram feature is extracted from FCMC segmented output. After the segmentation process, colour space conversion from HSV to RGB is done and surf features are extracted. Colour correlogram combines colour and spatial information (spatial colour correlation) and it expresses the colour change of pixels with respect to distance. A three dimensional table is created with entries like pairs of colours and distance. The entry (pairs of colours) (cj, ck) indicate the probability that the pixel p1 of colour is ck from the pixel p2 of colour cj with the distance between the pixels is | p1-p2 | . It consists of 3 steps: (i) Determining the number of pixels with colour c from the fixed pixel p within a given distance for both positive horizontal and vertical directions. (ii) Determining the number of pixels with colour ck from some coloured pixel cj within distance k (iii) Calculating the correlogram.

For extracting speeded up robust features (surf) colour conversion from HSV to RGB is done. The equations for converting HSV colour space to RGB are given below:

X = V *S -- (5)
Y = X * (1-| (H/60°) mod2-1 |) -- (6)
Z = V – X -- (7)

$$(R1,G1,B1)=\begin{cases}(X,Y,0) & ,0^\circ \le H < 60^\circ \\ (Y,X,0) & ,60^\circ \le H < 120^\circ \\ (0,X,Y) & ,120^\circ \le H < 180^\circ \\ (0,Y,X) & ,180^\circ \le H < 240^\circ \\ (Y,0,X) & ,240^\circ \le H < 300^\circ \\ (X,0,Y) & ,300^\circ \le H < 360^\circ \end{cases} \quad \text{-- (8)}$$

$$R = (R1+Z)*255 \quad \text{-- (9)}$$

$$G = (G1+Z)*255 \quad \text{-- (10)}$$

$$B = (B1+Z)*255 \quad \text{-- (11)}$$

Surf feature is computationally efficient with rotation and blurring images and it is very fast. It requires Hessian matrix to be evaluated for an image to make a note of minima & maxima linked with the region intensity and also it is a measure of intensity change around a particular point. The key points or features are selected based on the maximum value of determinant of Hessian matrix. The steps for finding Hessian matrix of an image (second order partial derivative of the image) are: (i) Choosing the smoothing function (ii) Evaluating the second order partial derivative of the smoothing function to generate the filtering mask (iii) Finding the convolution of image and the mask.

D. Classification of lesions using cascaded rotation forest classifier

Totally 300 fundus images have been taken for training and 400 images have been taken for testing Cascaded Rotation Forest (CRF) classifier. The classifier is chosen because it uses the concept of diversity and accuracy is more. In the training stage, the following steps are done: (i) Dividing the whole feature set into subsets (ii) Choosing bootstrap samples from the subsets (iii) Applying PCA to the bootstrap samples to collect coefficients for rotation matrix (iv) Create the rotation matrix. (v) Form ensemble classifier. In the testing stage, (i) Evaluating the confidence for each class for the given input. (ii) Assigning input to the class based on the largest confidence. Classifier output is given in Figure 6.

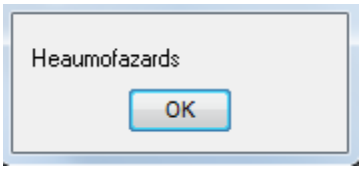

Fig. 6: Classifier output

IV. RESULTS AND DISCUSSION

The proposed system is able to detect early stage lesions in Diabetic Retinopathy such as Microaneurysms, Haemorrhages and exudates using Fuzzy C-Means Clustering algorithm. Morphological operations are used for pre-processing the colour fundus images. Cascaded Rotation Forest classifier is used for classification of lesions. Hybrid features like colour correlogram and SURF are used to train the classifier. Finally the sensitivity, specificity and accuracy performance of the CRF classifier have been analysed. It is realised that cascaded rotation forest classifier is giving tremendous classification results and it is shown in Fig. 7. The equations for finding sensitivity, specificity and accuracy of the classifier are given below and the values are shown in table 1. Also the results for various lesions are shown in Fig. 8.

$$\text{Sensitivity} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Negative})} \times 100 \quad \text{--- (12)}$$

True Positive - DR images correctly classified

False Negative - DR images classified as normal

$$\text{Specificity} = \frac{\text{True Negative}}{(\text{True Negative} + \text{False Positive})} \times 100 \quad \text{--- (13)}$$

True Negative - Normal images correctly identified

False Positive - Normal images incorrectly detected as DR

$$\text{Classifier Accuracy} = \frac{\text{Total number of outputs correctly identified}}{\text{Total number of test inputs}} \times 100 \quad \text{-- (14)}$$

TABLE 1: SENSITIVITY, SPECIFICITY AND ACCURACY OF THE CASCADED ROTATION FOREST CLASSIFIER

Classifier-Cascaded Rotation Forest	Input Images	Training Stage		Testing Stage		Accuracy (%)	Sensitivity (%)	Specificity (%)
		Total No of Inputs	No of correct trained outputs	Total No of inputs	No of Correct Test o/p			
	Normal	100	100	100	96	96	97	96
	DR	200	200	300	292	97		

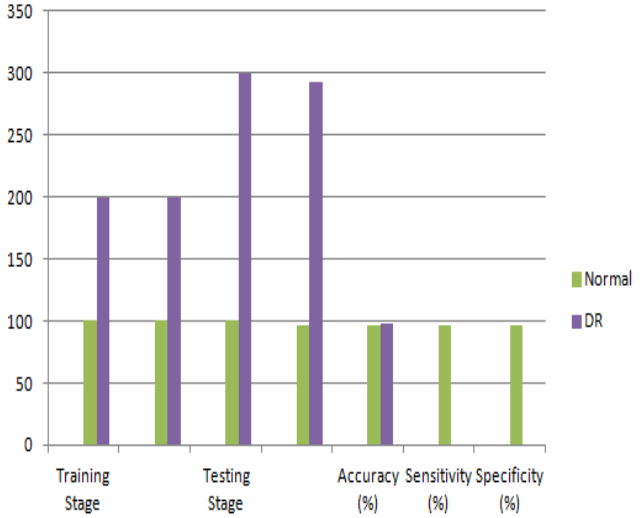

Fig. 7: Performance of CRF classifier

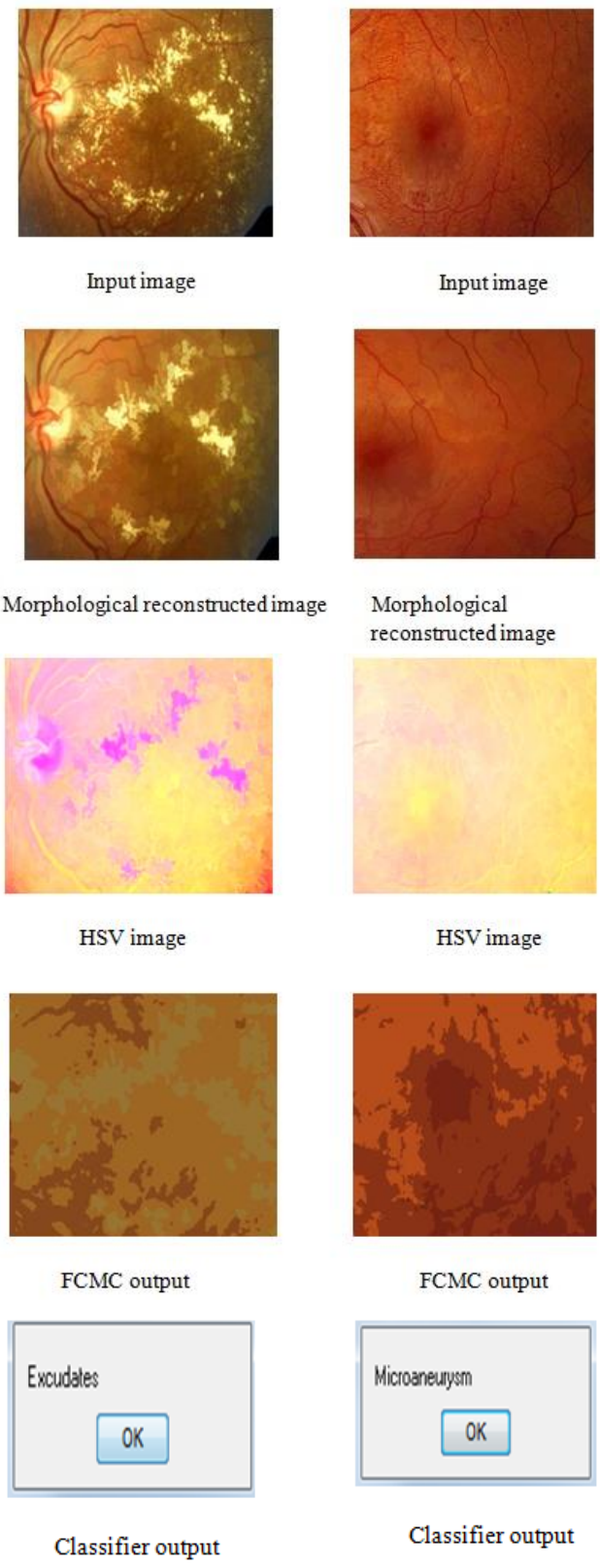

Fig. 8: Results for various lesions

V. CONCLUSIONS AND FUTURE ENHANCEMENTS

The proposed system has the potential to detect early stage lesions in the Diabetic Retinopathy. Most of the research works dealt with grey scale images and hence this method is developed to work with colour fundus images. This method works well for detecting all early stage lesions such as Microaneurysms, Haemorrhages and Exudates. Morphological pre-processing is effective in removing small unwanted details in colour fundus images. Hybrid features such as colour correlogram & speeded up robust features are used to train the classifier and cascaded rotation forest classifier effectively improves the accuracy by 97.3% and the total execution time is 13.91seconds. The sensitivity and specificity values are 97% and 96% respectively. This work can be expanded further to detect the lesions for proliferative diabetic retinopathy.

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