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Detection of Exudates in Retinal Images using back Propagation Neural Network

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ABSTRACT: A known fact for blindness is due to increase in the blood sugar level which causes exudates a major problem in visualization for older people. At the same time manual diagnosis involves a great deal of time for ophthalmologist. In this direction soft computing techniques will help in early diagnosing exudates. In this paper, authors have attempted to detect exudates using back propagation neural network by using around 100 images with standard resolution availed from the publicly available database DIARETDB. To classify the localized segmented image into exudates and Non-exudates, a number of image level features are extracted using Gray level Co-occurrence Matrix (GLCM) which is given as input to BPN. Experiments were conducted using different topologies with one hidden layers with 5 to 25 hidden nodes and different partitioning of Training, Validation and Test data like 40:30:30, 50:25:25 and 60:20:20. The experimental results indicate that the best performance of BPN was obtained for 9-20-2 topology with the accuracy level of around 94%.

KEYWORDS*:* Exudates, soft computing, GLCM features, back propagation neural network, localized segment.

I. INTRODUCTION

One of themultidisciplinary research areas is Medical images analysis, which includes processing an image, pattern recognition, visualization and Machine learning. Ophthalmologists are interpreted Retinal images in order to diagnose Diabetic Retinopathy (DR) particularly exudates. To make the diagnosis more efficiently and effectively retinal image analysis system can be developed for ophthalmologists to assist diagnosis. DR is the most common cause of blindness in the population (aged 25-65 years), and in most cases, it is treatable if the condition is effectively monitored. To protect vision, diabetic patient's eye examinations are needed every year as directed by the Ophthalmologists. If the number of diabetic patients increases more number of retinal images, need to be reviewed by the Ophthalmologists to screen for exudates, which is more time consuming. Different types of exudates are of different stages based on the size and growth for examples micro aneurysms, Hemorrhages hard Exudates and cotton wool spots. At the beginning stage of diabetic patients having small dotted spots called micro aneurysm. Normally these spots are in a group like cluster of red spots having tiny hemorrhages in and around fovea. These micro aneurysms are of different sizes ranging between 10-100 microns which is very less in size. Spot sizes are less than 1/12th the diameter of an average OD and most of these shapes are in circular shape. This is the beginning stage of the exudates. If the patients are not treated properly in this stage it will move to the next stage, tiny spots are widening because of leakage of the blood, yellow fluid that is rich in fat and protein lipid continuously. These big spots are called hard exudates. Hard exudates are of different sizes vary from tiny specks to large patches with clear edges. As the exudates are spreading towards the fovea region, light falling on the retina gets blocked leads to blockage of vision. By applying image processing techniques, features are extracted based on the textures in the fundus images. These features are used to detect the exudates by applying neural network techniques.

II. RELATED WORK

Exudates are formed due to the leakage of proteins and lipids from damaged blood vessels within the retina. Exudates are the early signs of Diabetic Retinopathy. If the exudates keep moving into the macular area, there may be a definite chance of occurring loss of vision. Many more automated methods have been tried for the detection of exudates like Support Vector Machine, K-Nearest Neighbor, K-Means Clustering, Naïve Bayes and other machine learning methods.Akara et al [1] mainly focuses on automatic detection of exudates in images acquired through non-dilated pupils using a Naïve-Bayes classifier. Preprocessing is done for transforming RGB into HSI color space, for reducing noise median filtering is applied and for improving contrast enhancement, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the I component of HSI image. Classification is done using Naïve-Bayes classifier by adopting the principle of Maximum a Posteriori (MAP) classification. The final classifier's overall sensitivity, specificity and accuracy were found to be 93.38%, 98.14% and 98.05% respectively.

Asha et.al [2] proposed a method of exudate detection in retinal images using KNNFP and WKNNFP. Preprocessing steps include RGB color space image is transformed to HSI color space, Median filtering is used to reduce noise and CLAHE is applied to the I component to improve contrast enhancement. The distance measures namely Euclidean and Manhattan distance are used for KNNFP and WKNNF. The performance measure for KNNFP is achieved with a sensitivity of 100% and 86.84%, specificity of 92.59% and 90.90%, accuracy of 96.67% and 88.33% for both distances correspondingly. Hussain et.al [3] proposed a method of grading hard exudates from retinal fundus images. Preprocessing steps involves smoothening of green component using filter stages; first by median filter followed by Gaussian filter. The shade correction is carried out using morphological operations.Edges in each region are detected using Canny Edge Detector. A classification process is carried out to classify hard exudates from non-hard exudates using rule-based classifier. The performance measure is achieved with a sensitivity of 98.4% and specificity of 90.5%. B.Ramasubramanian et.al [4] proposed a method for automatic detection of exudates and Diabetic Maculopathy in colour fundus images. The preprocessing steps involved are RGB image transformed to HSI color space, median filtering is applied to reduce noise and CLAHE is applied for contrast enhancement To classify the segmented region into exudates and non-exudates SVM classifier is used. The success rate of detection of exudates is 97%. Annie et.al [5] describes an approach for exudate detection using clustering algorithm. Basic steps include transformation of RGB color space to HSI, Filtering technique used to remove the noise is the median filter. CLAHE is applied on the I component. The selected features are fed into SVM classifier which classifies exudates and non-exudates. The success rate achieved is 96%. Selvathi et.al [6] presented an automated detection of diabetic retinopathy using support vector machine. Segmentation of blood vessels is done by discrete wavelet transform of green channel image and coefficients are modified by a non-linear equation. Feature used for classification is pixel intensity consisting of eight connected neighbours. The extracted features are given to the SVM for classification based segmentation. UmerAftab et.al [7] presented an automated identification of exudates for detection of Macular Edema. The presented method consists of mainly three stages i.e. candidate exudate detection, feature extraction and classification. For candidate exudate detection, morphological closing operator is used to smooth dark regions such as haemorrhages and blood vessels. Gabor filter bank is used for the detection of bright regions and represented by Gaussian kernel function. Gaussian mixture model based classifier is used to divide regions into two classes' exudates and non-exudates. The proposed method achieves a sensitivity of 96.36% and specificity of 98.25%.Karthikeyan et.al [8] presented various methodologies to detect and quantify lesions associated with diabetic retinopathy as well as classification schemes for classifying the severity of DR. In the pre-processing step, RGB color image is considered, second derivative Gaussian filter is used and histogram equalization is used for contrast enhancement Atul Kumar et al [9] proposed a method for the implementation of a segment based technique for detecting exudates from retinal images. The methodology is composed of morphological operation with the SVM algorithm. Preprocessing step includes image normalization to remove differences in brightness correction; contrast enhancement, color modification from the Original images, RGB image is transformed to Gray scaled image and CLAHE is applied to improve contrast enhancement This method has achieved sensitivity and specificity as 97.1% and 98.3% respectively. Kittipol et.al [10] presented an automatic detection of retinal exudates using Support vector machine. Preprocessing steps are color normalization using histogram specification on individual RGB color space, local contrast enhancement , median filter is used to remove noise, color space such as RGB, YIQ HSI, HSL, Lab, Luv are selected for classification approach , out of these Luv appeared the most suitable color space for segmentation. SVM classifier is used for pixel based classification and achieved a sensitivity of 94.46%, specificity of 89.92% and overall accuracy of 92.14%.

III. MATERIALS AND METHODS

Fundus photography is used for taking photograph of the internal surface of an eye, which includes the retina, optic disc, macula, and posterior pole. This image of the retina is acquired with the digital camera, which is a specialized high resolution camera. Images are collected from the online data base DIARETDB1 and some images are collected from private hospitals used for testing and validation purpose.

In this database different images along with annotation file is also available in which grading of the DR result for each image such as grading of retinopathy such as micro aneurysm, exudates, hemorrhages, neovascularization. In this work the publicly available diabetic retinopathy dataset DIARETDB1 has been used in this work along with some samples from different hospitals. This database contains 89 images with pixel intensity 1500×1152. Out of 89 only 47 images are of exudates and remaining are normal or other types of abnormalities. Authors used these images by scaling 256X 256 sizes for their experimental work.

A. *Image Preprocessing*

Collected images are of having different ranges in Luminosity, contrast and brightness make it difficult to extract retinal textual features and also look complex in distinction of hard exudates from other bright features in images. As the first step preprocessing is done to remove the noise and equalization of the irregular illumination associated with images is also done. The stages of image preprocessing applied in this work are detailed below.

B. *RGB to HIS color space conversion*

In this space conversion an RGB image of M x N x 3 array of color pixels, in which each pixel consists of triplet which corresponds to Red, Green and Blue components of RGB image. Other color spaces include HSI, NISC, HSV, CMY, YcbCr, and color spaces [11, 12]. At the first step of preprocessing the original RGB image is transformed to HSI (hue, saturation and intensity) color space. The HIS color space is commonly used for color model, which helps in senses colors as did in the normal eye.

HIS color space is selected because the intensity represented in matrix form of the image also separated from other components such as Hue and saturation. So the highly significant data helps for diagnosing of hard exudates having big patches present only in the intensity matrix. This matrix contains intensity values, SD of intensity, distance between OD and mean pixel value, and also exudates and non-exudates pixel values can be extracted. Hue is the color space property which gives the purity of the color. Saturation gives the measure of white light mixed with the hue color. The intensity, lightness or the value related to the color luminance. The transformation equation used in the conversion of RGB to HIS is given below:

$$I\ (\text{or } V) = \frac{1}{3}(R+G+B)$$

$$S = 1 - \frac{\min\{R,G,B\}}{I}$$

$$H = \begin{cases} \delta & \text{if } B < G \\ 360-\delta & \text{otherwise} \end{cases} \quad \text{where } \delta = \cos^{-1}\left(\frac{0.5\left((R-G)+(R-B)\right)}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right)$$

If S = 0, H is meaningless.

If (B/I) > (G/I) then H = 360 - H since H is an angle in degrees we then normalize to 0, 1 With H=H/360

Saturation component is given by:

S= 1 - [3 (R + G + B)][min (R , G , B)]

Finally, the Intensity Component is given by

I = 1/ 3 (R + G + B)

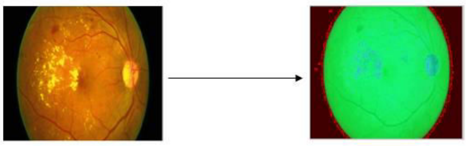

Fig1:RGB to HSI Conversion

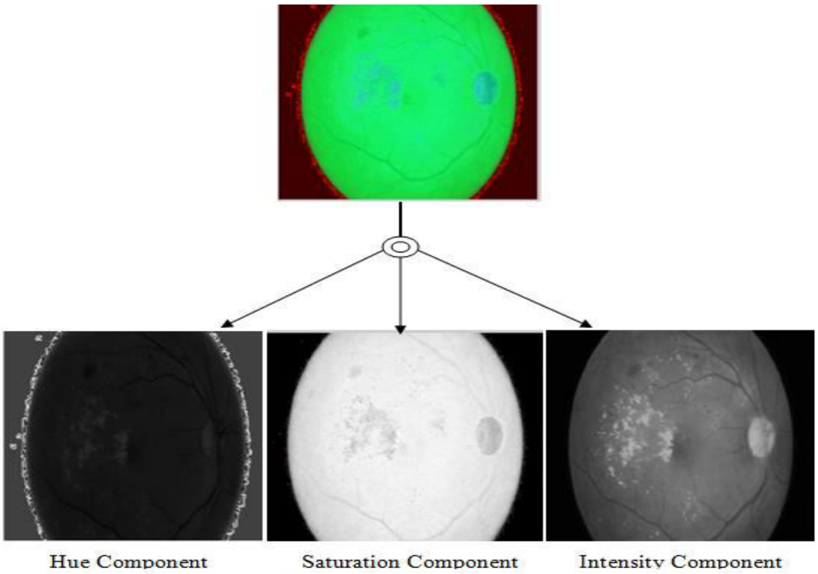

Fig 2: HSI Components

C. *Median Filter*

One of the efficient filters for suppressing isolated noise without disturbing i.e. blurring sharp edges is the Median filter.

$$f(x,y) = \underset{(s,t)\in S_{xy}}{\text{median}}\{g(s,t)\}$$

It keeps replaces the pixel value by the median of the pixels values in the neighborhood sliding window. Median filter is the best filter for removing salt and pepper type of noises [13].
As a part of preprocessing, salt and pepper noise is added to intensity to remove more clusters of noises by applying median filter of 3X3 size.

D. *Adaptive Histogram Equalization*

Uneven illumination is the major problem in image analysis as some areas are too brighter than other areas.
Brighter is more in the center of the image as compared with the edges having poor illumination and appears to be dark. Illumination keeps on increasing as distance from the centre of the image decreases. In the literature survey it is found that many methods have tried to resolve un-even illumination. Among these methods Adaptive Histogram Equalization Method (AHEM) found to be the best. So in our work we tried AHEM, which gives better performance, higher processing speed and work well for all the images of different sizes [14].

E. *Optic Disk Elimination*

OD is having bright intensity similar to hard exudates intensity. Cropping of OD is challenging to avoid false positive results. Select ROI i.e. OD using mat lab function and carefully crop the OD manually say I1. This can be done by using roipoly() function. Further binary image with size 256x256 with all the ones are taken say I2. I1 is subtracted from I2 to get the new image called I3. The image I3 is multiplied with preprocessed Intensity image I, which gives the image without optic disc. The procedural figures are shown below.

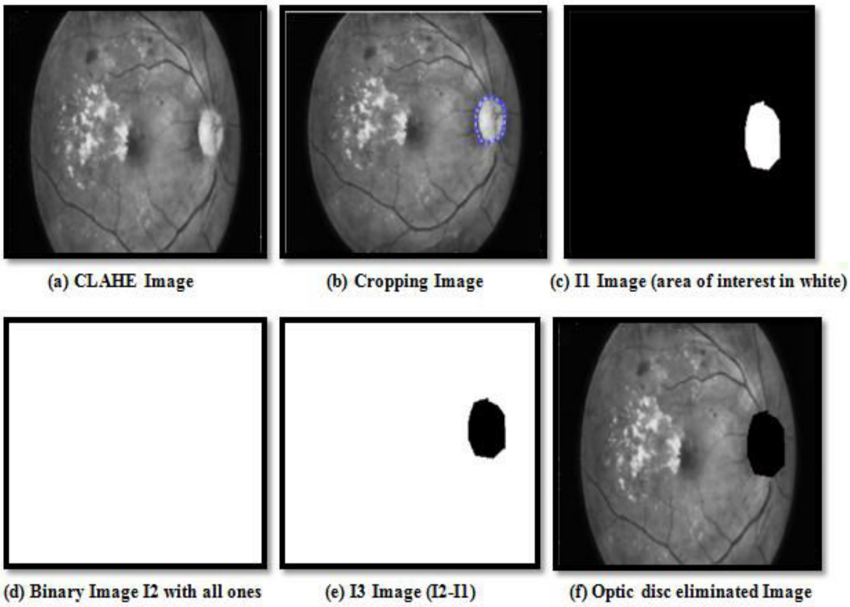

Fig 3: Image Processing

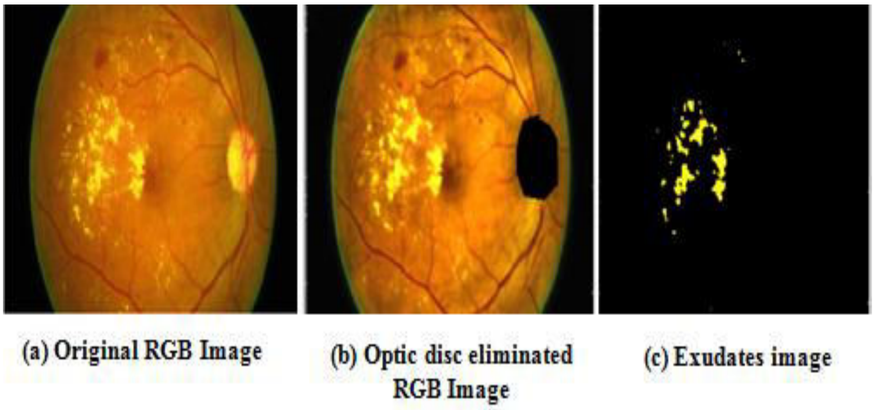

Fig 4: Exudates Detection

IV. FEATURE EXTRACTION

To identify the segmented image into exudates and non-exudates number of features of image level are extracted and stored in matrix form called Gray level Co-occurrence Matrix (GLCM)[15]. The features extracted were contrast, correlation, energy, cluster shade, homogeneity, dissimilarity, sum variance, difference variance and entropy. The extracted feature values are tabulated in the table 1.

Contrast	Correlation	Cluster shade	Dissimilarity	Energy	Entropy	Homogeneity	Sum variance	Difference variance
0.088	6.89	0.018	0.985	0.063	0.996	4.636	0.088	-0.477
0.589	47.21	0.097	0.933	0.218	0.984	8.603	0.589	-0.473
0.035	6.11	0.006	0.993	0.026	0.998	4.511	0.035	-0.695
0.207	15.09	0.0467	0.962	0.149	0.989	5.511	0.207	-0.442
0.084	15.48	0.017	0.978	0.087	0.996	5.417	0.084	-0.651
0.274	16.35	0.050	0.968	0.121	0.991	5.597	0.274	-0.421

V. CLASSIFICATION USING BPN

Feed forward topology is used in BPN as errors are propagated back until the proper results reached. The learning algorithm is supervised as it classified based on the predefined class labels.
This algorithm was responsible in large part for the re-emergence of neural networks in the mid-1980s. Back propagation is a general purpose learning algorithm. It is powerful but also expensive in terms of computational requirements for training. [16,17]. The steps followed in this work is shown in the below flow diagram

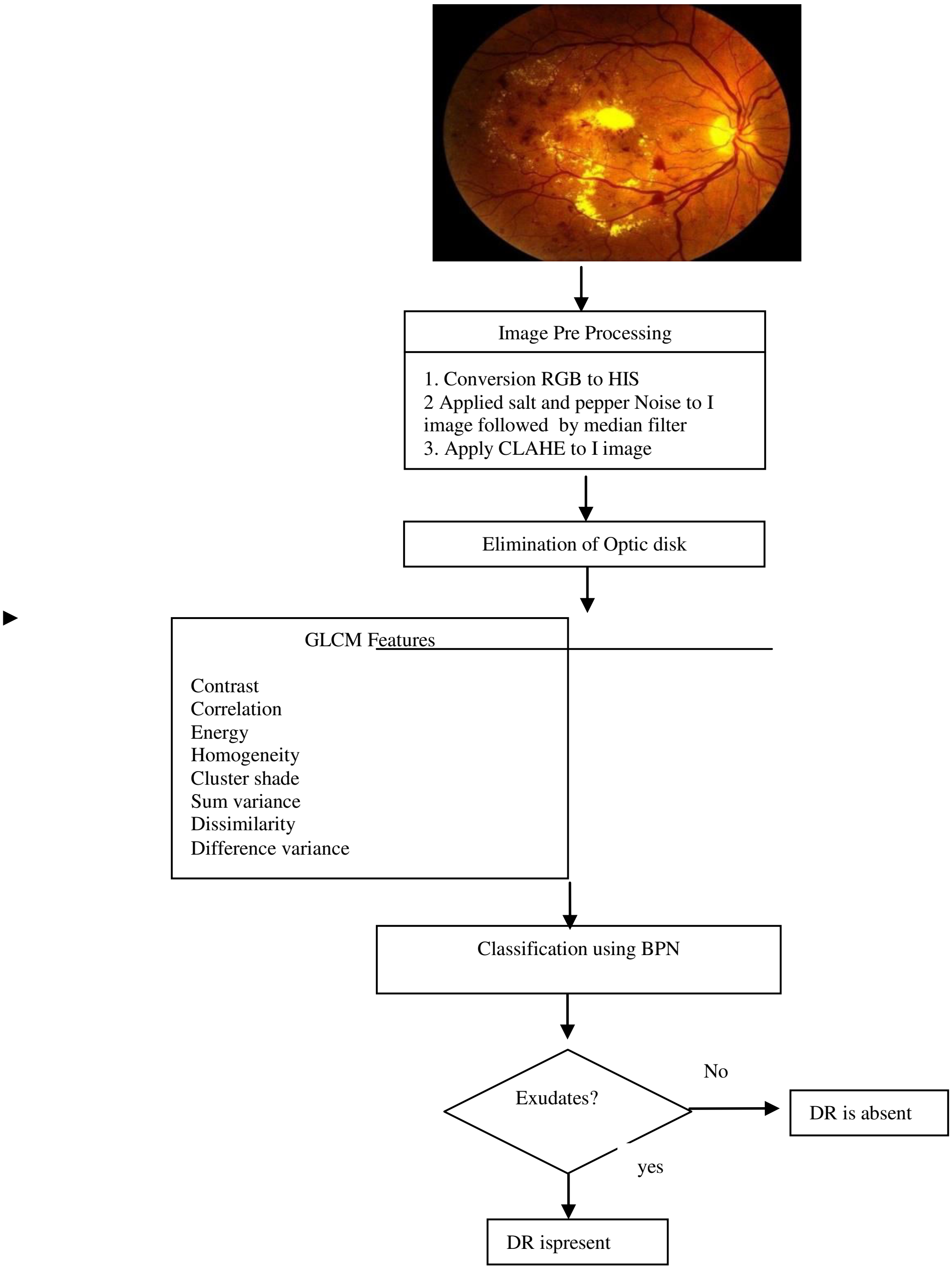

Fig 5: Flow diagram for Exudate detection

As the image is loaded from the data base, the first step is to preprocess the image to remove the noise and do the histogram equalization to have the equal illumination. In the second step eliminate the OD as it similar to exudates. Then extract the GLCM features from all the images and stored in the table. In the final step feed all the features to

BPN model for the purpose of classification. The entire date set is divided into different partitions for training, testing and validation by varying different topology.

VI. RESULTS AND DISCUSSION

Experiments were conducted using different topologies with one hidden layers with 5 to 25 hidden nodes and different partitioning of Training, Validation and Test data like 40:30:30, 50:25:25 and 60:20:20. Number of epochs experimented was 10 to 50 epochs. The other network parameters were kept constant with step size for gradient descent as 0.1, weight change momentum as 0.6 and error tolerance as 0.01. The best classification accuracy achieved around 94.3% for 9-20-2 topology with 21 epochs. Table 2, 3 and Table 4 shows results for different Partitioning of data with different number of hidden nodes Table 1 gives the details of the GLCM features.

NN Topology	Train Accuracy	Test Accuracy	Validation Accuracy	Average Accuracy	No. of Iterations
9-5-2	86%	84%	82%	84.0%	32
9-10-2	88%	86%	84%	86.0%	24
9-15-2	90%	88%	87%	88.3%	50
9-20-2	92%	90%	89%	93.3%	48
9-25-2	90%	89%	87%	88.6%	42

Table 2: Performance of BPN for 40:30:30 partitioning of data

NN Topology	Train Accuracy	Test Accuracy	Validation Accuracy	Average Accuracy	No. of Iterations
9-5-2	90%	87%	85%	87.3%	26
9-10-2	90%	88%	87%	88.3%	35
9-15-2	91%	86%	84%	87.0%	41
9-20-2	95%	93%	91%	93.0%	22
9-25-2	93%	92%	89%	91.3%	42

Table 3: Performance of BPN for 50:25:25 partitioning of data

NN Topology	Train Accuracy	Test Accuracy	Validation Accuracy	Average Accuracy	No. of Iterations
9-5-2	90%	88%	86%	88.0%	23
9-10-2	92%	90%	89%	90.3%	38
9-15-2	93%	91%	90%	91.3%	49
9-20-2	96%	94%	93%	94.3%	21
9-25-2	94%	92%	91%	92.3%	40

Table 3: Performance of BPN for 60:20:20 partitioning of data

VII. CONCLUSIONS

In this study we explored BPN method towards the development of an automated decision support system for the purpose of detecting exudates using GLCM features. Detection and timely treatment of DR can slow down the progression of the disease. The blindness can be avoided if detected in early stages through regular checkups and follow-up. With limited staff the automated detection system is used by lab techniques to indicate which patient requires more investigation and refers to an ophthalmologist for further investigation. The development of automated system by using GLCM features can be effectively used as a filter of normal images, thereby reducing the burden on eye specialists, in addition the improvement of efficiency of diabetic screening program and reduction of cost. One of the best methods used is the BPN to train feed forward neural network to identify the exudates and classify as exudates and non-exudates.

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