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Detection Of Cotton Wool Spots In Retinopathy Images: A Review

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Abstract : *Cotton wool spots are retinal lesions which appear as yellowish or whitish patches with not so well defined edges. Cotton wool spots are closely associated with Hypertensive Retinopathy. Hypertensive Retinopathy is a disturbance in the retina of the eye caused by high blood pressure. Common symptoms of hypertensive retinopathy are arteriolar narrowing, retinal hemorrhages and cotton wool spots. Early diagnosis of hypertensive retinopathy is possible for prevention and accurate treatment. This paper presents an exhaustive review of the various latest trends to detect Hypertensive Retinopathy condition based on computer aided diagnosis screening systems to automated and integrated Diabetic Retinopathy detection and monitoring system. This paper also presents the performance comparison of various predecessors Diabetic Retinopathy detection systems based on quality metrics, such as sensitivity, specificity and accuracy. Moreover this review paper will assist to researcher to quickly analyze the latest trend of various Diabetic Retinopathy and Hypertensive Retinopathy screening methodologists in medical engineering. . The recent methods used to detect cotton wool spots and retinal exudates are discussed. Also we discuss the automated detection of Cotton wool spots in Hypertensive Retinopathy using image processing methods. Methodologies used by the researches in analyzing their results are also discussed.*

Keywords - *Cotton Wool Spots (CWS), Hypertensive Retinopathy (HR), Image Processing, Retinal Image.*

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I. Introduction

The retina is the tissue layer located at the back of the eye that transforms light into nerve signals that are the sent to the brain for interpretation. Retinopathy refers to the damage to the retina of the eye which may lead to vision impairment or vision loss. Retinopathy is often seen in diabetes or hypertension. Constant elevated blood pressure causes the retina's blood vessel walls thicken and narrow. This puts pressure on the optic nerve and cause vision problems. This condition is called hypertensive retinopathy (HR) [12]. The contributing signs of HR include the appearance of hard exudates and soft exudates. Soft exudates are also known as Cotton Wool Spots (CWS). Cotton wool spots are the abnormal findings on funduscopic exam of the retina of the eye. These are small, yellowish-white or grayish-white slightly elevated lessions which looks like clouds. As such their edges are blurry and not defined. On the other hand hard exudates are small white or yellowish white deposits with sharp margins. Hypertensive Retinopathy exhibits a drier retina with more Cotton Wool Spots and less exudates and/or hemorrhages [14]. Cotton wool spots are closely associated with Hypertensive Retinopathy rather than Diabetic Retinopathy [13]. Image processing plays a vital role in automated diagnosis of different diseases of the retina nowadays. It provides a non invasive method for the detection of various retinal diseases such as hypertensive retinopathy, diabetic retinopathy etc. The detection result will help out to take the fast decision for automatic referrals to the ophthalmologists. Detection of contributing signs of a diseased retina from the fundus image helps in early diagnosis of the disease and necessary treatment can be carried on further thus reducing vision loss of the victim.

Detection of these features is done from fundus images. The fundus images are taken from a special type of camera called fundus cameras. The detection of the mentioned features from the fundus images helps the ophthalmologists to decide on the severity of the HR and advise the required treatment to the patients. Also several methods and systems have been proposed for the detection of lessions in diabetic retinopathy but few methods have been proposed in case of hypertensive retinopathy. Most of the works on retinal images are focused on exudates detection, mainly on hard exudates. It is challenging to differentiate the CWS from other exudates and limited work has been done on CWS. A retinal image showing the difference of CWS and Hard Exudates (HE) is shown in Figure. 1.

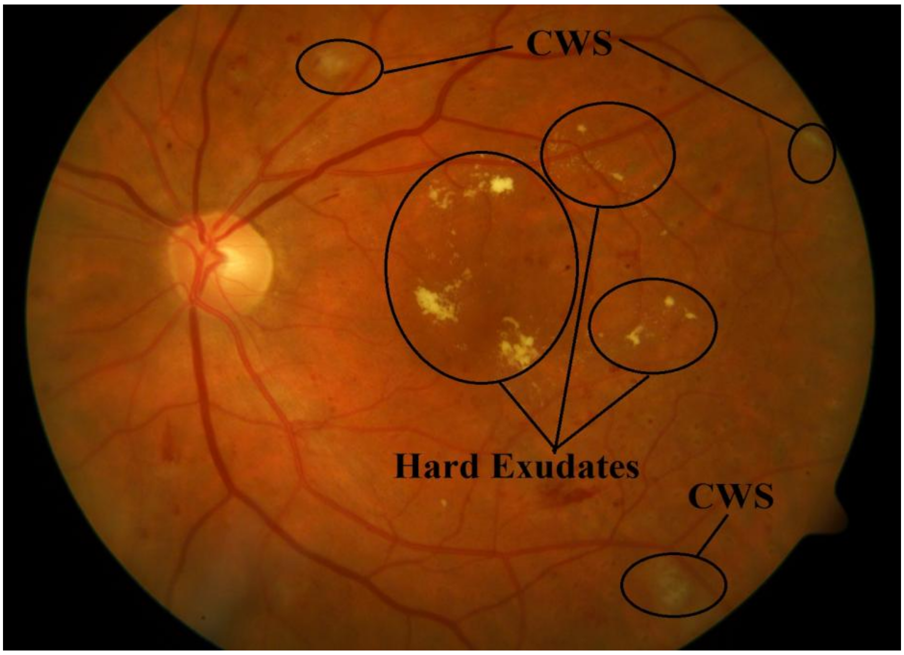

Figure 1: Retinal image having CWS (Source: Diarect DB1 database).

The remaining part of this paper is systematized in the following way: Section II documents the previous related works on detecting cotton wool spots in fundus retinal images. In section III, summary of the experimental results and efficiency or performance of the system, are tabulated and discussed. Finally, section IV concludes the paper.

II. Literature Review

The previous related works on cotton wool spots in case of retinopathy are discussed below:

Irshad et al. [1] presented an automated system for cotton wool spots detection in 2014 and achieved sensitivity of 82.16%. The system was evaluated using a database of 30 images of size 1504x1000 acquired from Ophthalmology department of AFIO, Pakistan.

In his method, the input image is pre-processed where the green channel is selected and median filtering [15] is used to suppress the noise in the image before eliminating high contrast structures like blood vessels and hemorrhages using morphological closing operation, where a disc shaped structuring element with a fixed radius of eleven is applied to green channel median filtered image. For enhancement of CWS, the image is passed through Gabor filter bank of different scale and orientations [16]. The filter bank is created based on Gabor based kernel is given in equation 1.

$$G_{FB} = \frac{1}{\sqrt{\pi r \sigma}} e^{-\frac{1}{2}[(\frac{d_1}{\sigma})^2 + (\frac{d_2}{\sigma})^2]} (d_1(\cos\Omega + \sin\Omega)) \qquad (1)$$

where σ, Ω, r and θ are the variation, frequency, aspect ratio and orientation respectively.

The filter bank enhances bright regions like CWS, OD and other lesions. The resultant image is thresholded to get a binary image. Later OD and other spurious regions are removed. The proposed system did not consider the images which do not have CWS since classification is not used. The results of proposed methodology are shown in Figure. 2.

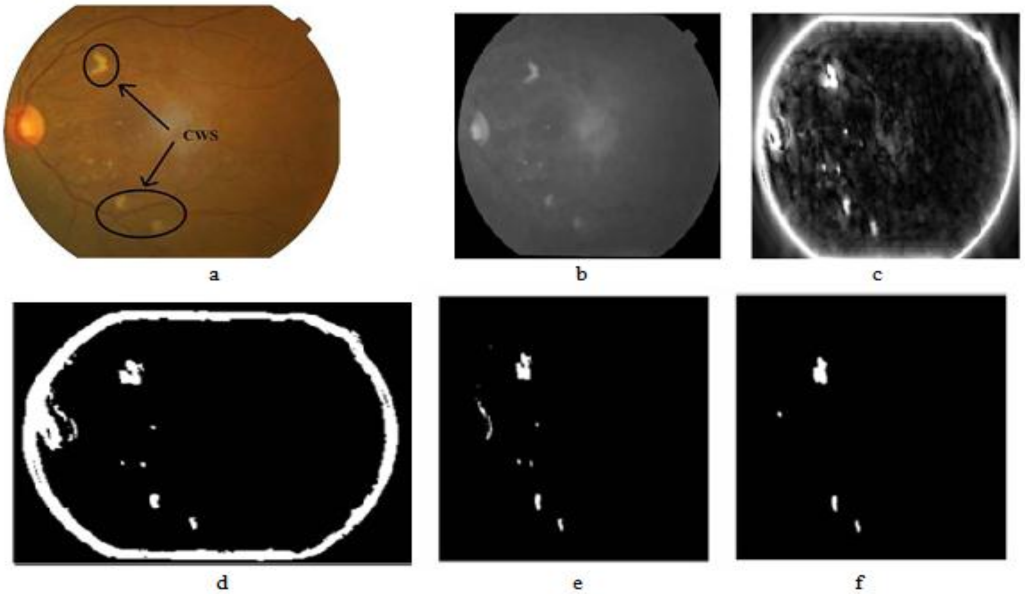

Figure 2: (a) Original Image (b) Morphological closed image (c) Gabor-filtered enhanced image (d) Thresholded image (e) Binary image after removing border and OD (f) Image after removing isolated small regions .[1]

Roy Chowdhury et al. [2] presented an algorithm to detect CWS automatically in 2015 using Fuzzy C means, tested on 20 images which can be accessed publicly.

In his method the input retinal image containing CWS is converted to gray scale and then pre-processed with contrast enhancement to make the image clearer and cotton wool spots get prominent. Then the position of the optic disc (OD) is detected considering it to be the brightest point in the image and depending upon this point a mask image is formed. The retinal image contains three colours - Dark red for the blood vessel tree, whitish yellow or very bright yellow for the Optic Disc (OD) and Cotton Wool Spots and yellowish red for the rest part that is mucus and membrane of retina. Segmentation is done using fcm function where the number of cluster is set to three. After segmentation is applied, three regions get three different colours. Using the coordinate position of OD, the particular region is extracted. This extracted portion contains CWS along with OD but the blood vessel tree and the empty area of retina is removed. For extracting the CWS, a mask image is used to cover the OD. Figure 3 shows the images obtained in the different stages of execution of the algorithm on retinal image containing CWS.

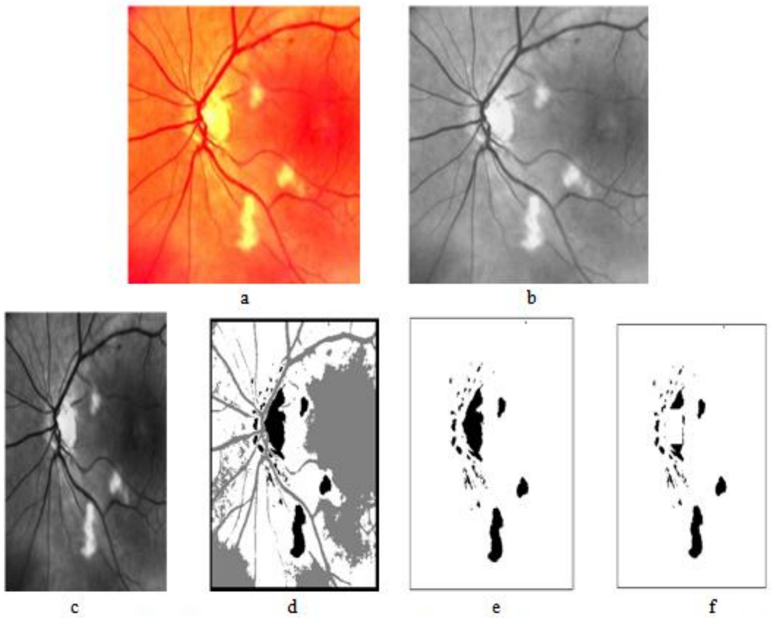

Figure 3: (a) Input image with CWS (b) Image in gray scale (c) Pre-processed image (d) Segmented image by FCM (e) Pre-processed image (f) Segmented image by FCM [2]

Rajput et al. [3] proposed an algorithm in 2015 for the extraction of CWS lessions applied on fundus images databases of total 1191 fundus images from STARE, DRIVE, DiarectDB0, DiarectDB1 and SASWADE (local database). Firstly the fundus image is read from the fundus image database, and then optic disc is removed from all fundus images. The green channel is extracted for removing the optic disc. For enhancement of image, histogram equalization is applied. Complement function and intensity transformation is applied to remove the optic disc. Then multi resolution analysis techniques using symlet wavelet (sym4) is applied for extraction of lesion. Feature extraction is done by using area, diameter, length and thickness of cotton wool spots. After feature extraction K-Means clustering is applied for classification feature data.

A multiresolution analysis of L^2 (IR)is a sequence of closed subspaces $V_j \subset$ L2 (IR) such that :

$V_j \subset V_{j+1}, \bigcap_j V_j = \{0\}$, $\bigcup_j^{-} = L^2$ (IR (2)

f (x) ∈ V0 ⇔ f (x ⇔ 1) €∈V0,

f (x) ∈V j ⇔ f (2x) ∈ Vj+1 (3)

A scaling function $\Psi \in V_0$ with unit integral exists such that { $\Psi_{0,k}$ (x) ≡ Ψ(x⇔k) , k ∈ Z}is an orthonormal basis of 0 and, consequently, the set of functions.

$\Psi_{j,k}$ (x)=$2^{\frac{j}{2}}$Ψ (2^j x⇔k) (4)

is an orthonormal basis of the space Vj , Since $\Psi \in V_0 \subset V_1$,a sequence of complex-valued coefficients a^k exists such that $\sum a^k$ = 1 and

$$\Psi(x) = 2\sum_k a_k \Psi(2x⇔k) \quad (5)$$

The proposed algorithm achieves 92% accuracy.

Niemeijer et al. [4] proposed machine learning based automated system in 2007 to detect exudates and cotton-wool spots in digital color fundus photographs, and differentiate them from drusen, for early diagnosis of diabetic retinopathy from a total of 430 retinal images from the Eye Check project in the Netherlands.

The machine learning algorithm is a so-called supervised algorithm, and therefore needed a set of annotated lesions to learn how to detect bright lesions and differentiate among them. For this purpose, 130 anonymous images originally read as containing bright lesions were selected. All pixels in all of these images were segmented by retinal specialist A as to whether they were (part of) an exudate, cotton-wool spot, drusen or background retina. Vessels, disc and red lesions, if present, were treated as background retina. In the machine learning algorithm the steps were as follows,

Each pixel was classified, resulting in a so-called lesion probability map that indicates the probability of each pixel to be part of a bright lesion. Then pixels were grouped into probable lesion pixel clusters having high probability. Each probable lesion pixel cluster was assigned a probability indicating the likelihood that the pixel cluster was a true bright lesion. Later each bright lesion cluster likely to be a bright lesion was classified as exudate, cotton wool spot or drusen. The automated system achieved sensitivity/specificity of 0.95/0.88 for the detection all bright lesions, and 0.95/0.86,0.70/0.93 and 0.77/0.88 for the detection of exudates, cotton wool spots and drusen respectively.

U.M.Akram et al. [5] in 2011 presented an algorithm using proposed Hybrid Fuzzy classifier that is performed on databases from DRIVE, STARE, DiaretDB0 and DiaretDB1 of 20 images for bright lessions. The algorithm is implemented for the detection of different DR lesions. As such blood vessels and optic disc are segmented out that hinders the further classification of different DR. The first step of the proposed system is pre-processing so as to improve and enhance the quality of the retinal image. After pre-processing, task is performed to enhance and segment the blood vessels by using Gabor wavelet and multilayered thresholding respectively. Then using average filter and Hough transform and edge detection, optic disc localization and the optic disk boundary is detected. After the segmentation of blood vessels and OD, dark and bright lesions are detected using hybrid fuzzy classifier. In this paper different distinguishable properties such as color, size and shape etc are considered to form the feature input vector. The feature vector set for classification of the lesions is formed by considering the area, mean hue, mean saturation, mean value, eccentricity and mean gradient magnitude of the candidate lesions. The proposed system gave accuracy of 94.73%.for bright lesions.

Osareh et al. [6] in 2003 presented a method for the identification of the retinal exudates from a total of 142 colour retinal images as the initial dataset. Out of these 142 dataset with resolution 760 x 657, 75 images were employed for training and testing the Neural Network in the exudate based classification stage and 67 images were used for the identification of images having any evidence of retinopathy.

In the pre-processing step, histogram specification and local contrast enhancement was implemented for further segmentation of the images that was applied on the I plane of the HSI colour model. For segmentation of the pre-processed image Fuzzy C Means (FCM) clustering method is used. An Artificial Neural Network (ANN) was applied for classification of exudates and non exudates.

The proposed system achieved accuracy with 95.0% sensitivity and 88.9% specificity in the identification of images having any evidence of retinopathy and 93.0%sensitivity and 94.1% specificity in the classification of exudates and non exudates. Figure. 4 shows the segmentation of the method proposed here.

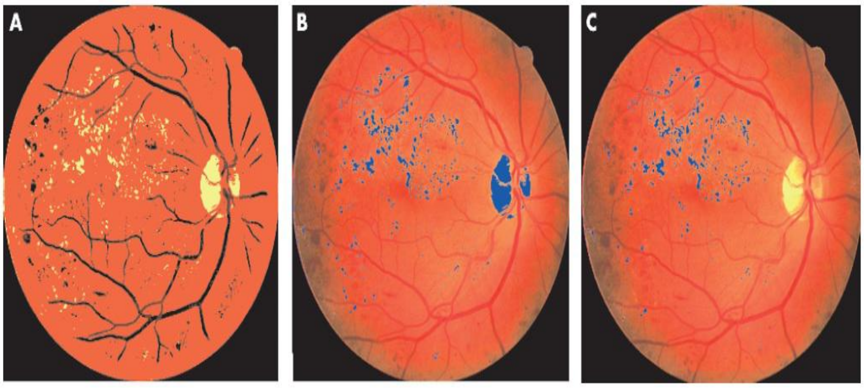

Figure 4: Colour image segmentation: (A) FCM segmented image, (B) Candidate exudate regions overlaid on the original image, and (C) Final classification (after subsequent neural network classification).[6]

Ranamuka et al. [7] presented a method for the identification of the exudates in 2013 and classification of the exudates and non exudates using fuzzy logic. The databases were obtained from Kuopio University hospital with a size of 1500X1152. 40 images from the publicly available Diabetic Retinopathy (DR) dataset DIARETDB0 and DIARETDB1 were chosen for testing the algorithm.

At first using morphological operations the optic disc is eliminated and exudates are identified. Further based on RGB values of the retinal image, fuzzy logic algorithm is implemented for the extraction of the hard exudates. Furthermore the output of the fuzzy logic is compared with the hand drawn ground truths and was able to detect hard exudates with sensitivity/specificity 75.43 and 99.99% respectively.

Prabha et al. [8] in 2016 has presented a paper image clustering method (hybrid) that helps to detect exudates presence in retina. In this proposed work, input image is obtained from the DIARETDBI database. It mainly contains four main processes and they are pre-processing, contrast enhancement, feature extraction and classification. In pre - processing method the background noise is removed and also the dark abnormalities are removed. In this process also the rgbcolor space of the retinal image is converted to Lab color space for the easiness of applying grey scale methods. Next replacing the noise and dark abnormality is done by Gaussian filter which removes most of the noise and it is advanced than any other filter. The general equation for this is :

$$G(x) = [1/\sqrt{2\pi\sigma}]e^{\frac{-x2+y2}{2\sigma2}} \quad (6)$$

For image enhancement where adaptive histogram equalization method is used which comparatively gives better result than normal histogram equalization technique. In feature extraction it extracts features like texture, size and edge and finally classification is done by clustering (Hybrid algorithm). The process used regionprops of matlab to measure the image region and then for the finding of the edge feature, canny operator is used. To find the texture, 16gabor filters are used which gives different orientation and angle value of the retinal image which could be taken from various angle. The last step is segmentation by use of hybrid method here two methods are used for the detection of exudates and they are hierarchical algorithm and mean shift algorithm. The proposed method showed high accuracy of 99.2% and the sensitivity is 97.1%.

Hazra et al. [9] in 2016 proposed an algorithm to detect the blood vessels and segment the hard exudates efficiently using thresholding technique, basic morphological operations and Kirschs edge detection operator. In the proposed system 15 retinal images with exudates (diagnosed with diabetic retinopathy, macular edema, etc.) and 5 normal retinal images without exudates were taken from DRIVE database.

At first the green channel is converted to the double precision image prior to the conversion of this into gray scale. For contrast enhancement, Adaptive Histogram Equalization is applied on the grayscale image. The image is binarized by applying thresholding using Otsu’s algorithm. The blood vessels are extracted using Kirsch’s template operator. Then median filter is applied to remove the noise from extracted blood vessels. Then the resultant image is subtracted from the thresholded image using Otsu’s algorithm to get the hard exudate region.

In this presented work, the thick vessels are detected by the Adaptive Histogram Equalization technique. Exudates were detected using thresholding by applying the Otsu’s algorithm. Kirsch’s template operator is used for extracting blood vessel.

In the Otsu’s method comprehensive search is carried for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$\sigma_{\omega}^{2}(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t) \qquad (7)$$

Weights ω_0 , ω_1 are the probabilities of the two classes which are separated by a threshold t and σ_0^2, σ_1^2 are variances of these two classes. The class probability $\omega_{0,1}(t)$ is then computed from the L histograms:

$$\omega_0(t) = \sum_{i=0}^{t-1} p(i) \qquad (8)$$

$$\omega_t(t) = \sum_{i=t}^{L-1} p(i) \qquad (9)$$

Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance which is estimated in terms of class probabilities and class means: [18]

$$\sigma_b^2(t) = \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2 \qquad (10)$$

Here, the class mean $\mu_{0,1,T}$(t) is expressed as follows:

$$\mu_0(t) = \sum_{i=0}^{t-1} ip(i)/\omega_0 \qquad (11)$$

$$\mu_1(t) = \sum_{i=t}^{L-1} ip(i)/\omega_1 \qquad (12)$$

$$\mu_T = \sum_{i=0}^{L-1} ip(i) \qquad (13)$$

The Kirschs operator is the first order derivative which is used for edge enhancement and detection. It finds the maximum edge strength in a few preset directions. For edge detection, the operator uses eight templates, which are successively rotated by 45 degree. The gradient is calculated by convolution of the image using eight template impulse response arrays which lie in each and every pixel. Thus, the gradient of different directions is attained. The final gradient is the summation of the enhanced edges where all directions for RGB channel is taken into consideration:[17]

$$h_{n,m} = max_{z=1,2,\dots 8} \sum_{i=-1}^{1} \sum_{j=-1}^{1} g_{i,j}^{z} \cdot f_{n+i,m+j} \qquad (14)$$

Where z specifies the compass direction kernels as follows:

For $0^o\ g^{(1)} = \begin{bmatrix} +5 & -3 & -3 \\ +5 & 0 & -3 \\ +5 & -3 & -3 \end{bmatrix}$

For $45^o\ g^{(2)} = \begin{bmatrix} -3 & -3 & -3 \\ +5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$

For $90^o\ g^{(3)} = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ +5 & +5 & +5 \end{bmatrix}$

For $135^o\ g^{(4)} = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & +5 \\ -3 & +5 & +5 \end{bmatrix}$

For $180^o\ g^{(5)} = \begin{bmatrix} -3 & 0 & +5 \\ -3 & -3 & +5 \\ -3 & -3 & +5 \end{bmatrix}$

For $225^o\ g^{(6)} = \begin{bmatrix} -3 & +5 & +5 \\ -3 & 0 & +5 \\ -3 & -3 & -3 \end{bmatrix}$

For $2\ 70^o\ g^{(7)} = \begin{bmatrix} +5 & +5 & +5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$

For $315^o\ g^{(8)} = \begin{bmatrix} +5 & +5 & -3 \\ +5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$

Finally, the detected image is compared with the ground truth exudates regions and difference performance parameters like accuracy, specificity, sensitivity, PPV, PLR and misclassified proportions are measured to assess the algorithms efficiency. The proposed algorithm successfully detects exudates with an average of 98.47% accuracy, 54.67% sensitivity, 99.82% specificity, 88.62% PPV, 303.73 PLR and 0.17% misclassified. Figure 5 shows the outputs of the proposed methodology in detecting hard exudates. In this paper it is mentioned hard and soft exudates can be distinguished by their color and the sharpness of their border so this can be achieved by tuning the edge filter and feature selection. Figure. 5 shows the output of various stages in this paper.

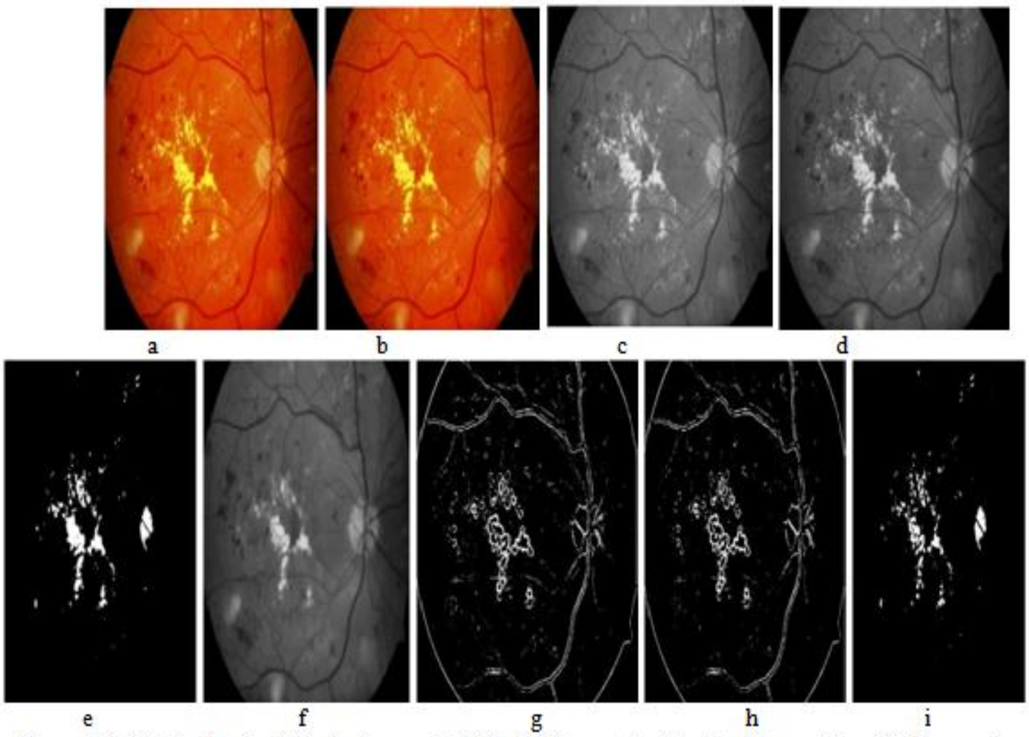

Figure 5: (a) Original retinal fundus image in RGB, (b) Conversion into double precision, (c) Gray scale conversion, (d) Image after adaptive histogram equalization, (e) Binarized image, obtained using Otsu's algorithm,(f) Opening on contrast enhanced image, (g) Extracted blood vessels using Kirschs templates, (h) Noise removal using median filtering, (i) Detected hard exudates. [9]

Maheswari et al. [10] in 2014 proposes a methodology for retinal lesion detection in Diabetic Retinopathy Images evaluated on two publicly available databases namely DRIVE AND STARE of a total of 40 and 81 images respectively.

In this paper the images are pre-processed followed by different DR lesions detection. The fundus images features viz: area of blood vessels, area of exudates, and area of microaneurysms are extracted along with texture properties that are passed through support vector machine (SVM) classifier which classifies the images into normal and abnormal classes.

For bright lesions segmentation morphological closing operation with an octagonal shaped structuring element is employed followed by edge detection using canny edge. Prior to the removal of circular border to fill the enclosed area, green channel image first finds the edges using canny method. Further circular border, edges and larger areas are removed. To make better visibility of the exudates the adaptive histogram equalization is applied twice. The bright features are then compared with the large area removed by using AND logic to get final exudates. Figure. 6 shows the illustration of exudate detection.

Figure 6: Bright lesion detection illustrated using STARE database (a) Input image (b) Exudates detected image [10]

The proposed method achieved sensitivity of 87.65% and specificity of 91.45%.

Jagatheesh et al. [11] in 2015 has proposed a system to detect and classify diabetic retinopathy lesions using Bag of Visual Words Model [19], [20]. Two different datasets, DR1 and DR2, were used. Out of 1077 retinal images 595 images normal images and 482 images have at least one disease, 234 images having hard exudates and 73 images having cotton wool spots were used. Dataset DR2 has 520 images out of which 300 are normal and 149 have at least one lesion, 79 images contain hard exudates and 17 images have CWS. In this paper DR lesions are detected using Bag Of Visual Words (BoVW) model. Speeded Up Robust Features (SURF) is used for extraction .For creating the visual dictionary K-Means clustering is used. Fisher vector encoding and Max pooling technique is used for creating Bag of Visual Words (BOVW). Furthermore for classification the lesion SVM is used. The accuracy obtained for detection of HE and CWS are 84.21% and 78.23% respectively.

III. Performance Comparison of the Cows Detection Methods

The summary of some of the related literature reviewed in the previous section is tabulated in Table 1. The table shows the database used along with the database population, methods used by the authors and their performance measure comparison.

Table 1: Performance Comparison of the CWS Detection Methods

AUTHOR	YEAR	DATABASE	DATABASE POPULATION	METHOD USED	PERFORMANCE MEASURE
Irshad et al	2014	Ophthalmology department of AFIO, Pakistan	30	Enhances candidate region using Gabor filter bank, then binarize those regions using Global thresholding	Sensitivity=82.21% PPV=82.38%
Roy Chowdhury et al	2015	Publicly available database	20	Fuzzy C means	not specified
Rajput et al	2015	STARE,DRIVE, DIARETDB0, DIARETDB1 and SASAWADE	1191	Symlet wavelet (sym 4)	Accuracy=92%
Niemeijer et al	2007	Eye Check Project in the Netherlands	430	Machine learning algorithm	Sensitivity/ Specificity=0.70/0.93
U.M.Akram et al	2011	DRIVE,STARE, DIARETDB0,DIA RETDB1	20 for bright lessions HE,CWS	Hybrid Fuzzy Classifier	Accuracy=94.73%
A.Osareh et al	2003	Obtained from Canon CR6-45non-mydriatic retinal camera with a 45 of view as the initial image dataset	142	For segmentation of the pre-processed image Fuzzy C means clustering method is used. To classify the segmented regions into exudates and non exudates an artificial neural network classifier was investigated	Sensitivity=93.0% Specificity=94.1%
N.G. Ranamuka et al	2013	DIARETDB0, , DIARETDB1	40	Fuzzy logic	For detecting hard exudates Sensitivity=75.43% Specificity=99.99%
K. Prabha et al	2016	DIARETDB1	84	Classification is done by clustering(Hybrid algorithm)	Accuracy=99.2% Sensitivity=97.1%
S.Hazra et al	2016	DRIVE	15 with exudates and 5 without exudates	An algorithm that uses thresholding techniques, basic morphological operations and Kirsch's edge detection operator to detect the blood vessels and segment the hard exudates efficiently	Detects exudates with an average of 98.47% accuracy, 54.67% sensitivity, 99.82% specificity, 88.62%PPV, 303.73 PLR and 0.17% misclassified

Maheswari et al	2014	DRIVE,STARE	40 from DRIVE and 81 from STARE	A novel method for the automated identification of exudates pathologies in retinopathy fundus images based on computational intelligence technique which employs a sequential execution of morphological operators to extract fundus image features like vessels, red lesions, and white lesions together with texture feature analysis	Sensitivity=87.65% Specificity=91.45%
Jagatheesh et al	2015	Not specified	234 Hard exudates and 73 Cotton wool spots	Detection of Diabetic Retinopathy lesion using Bag of Visual Words and Speeded Up Robust Features for extraction	Accuracy : For Hard Exudates=84.21% Cotton wool spots=78.23%

IV. Conclusion

CWS are one of the important signs of HR. Through the study of various literature of detecting CWS, it is seen that CWS have blurred edges compared to other exudates. Feature based segmentation of the candidate region can be a scope for improvement of the accuracy of the detection of CWS.

References

[1]. S.Irshad, M.Akram, M.Salman and U.Yasin, Automated Detection of Cotton Wool Spots for the Diagnosis of Hypertensive Retinopathy, 7th Cairo International Biomedical Engineering Conference, December 11-13, 2014.
[2]. A.R.Chowdhury and S.Banerjee, Detection of Cotton Wool Spots from Retinal Images using Fuzzy C Means, International Journal of Computer Applications (0975- 8887),Volume 113, No. 11, March 2015.
[3]. Y.M.Rajput, R.R.Manza and M. B. Patwari, Extraction of Cotton Wool Spot using Multi Resolution Analysis and Classification using K Means Clustering, International Journal of Computer Applications in Technology, April 2015.
[4]. M. Niemeijer1, B.V. Ginneken, S. R. Russell, M. S.A. Suttorp- Schulte and M. D. Abrmoff, Automated Detection and Differentiation of Drusen, Exudates, and Cotton-wool Spots in Digital Color Fundus Photographs for Early Diagnosis of Diabetic Retinopathy, Invest Ophthalmol Vis Sci. 2007 May ;48(5): 2260-2267. doi:10.1167/iovs.06-0996.
[5]. U. M. Akram and S. A. Khan, Automated Detection of Dark and Bright Lesions in Retinal Images for Early Detection of Diabetic Retinopathy, Springer Science+Business Media, LLC 2011,Published online: 17 November 2011.
[6]. A.Osareh, M.Mirmehdi, B.Thomas and R.Markham, Automated identification of diabetic retinal exudates in digital colour images, Br J Ophthalmol 2003; 87:12201223.
[7]. N.G. Ranamuka and R. G. N. Meegama, Detection of hard exudates from diabetic retinopathy images using fuzzy logic, IET Image Process., pp. 110 1 doi: 10.1049/iet-ipr.2012.0134.
[8]. K. Prabha, J. Hemanth D, Detection Of Exudates in Retinal Images using Neural Network, International Conference on Engineering Innovations and Solutions (ICEIS 2016).
[9]. S.Hazra A. Patra and T.U. Paul, Exudates Detection of Retinal Images using Otsu's Thresholding and Kirschs Templates, IJCSN International Journal of Computer Science and Network, Volume 5, Issue 4, August2016.
[10]. M. S.Maheswari and A .Punnolil, A Novel Approach for Retinal Lesion Detection In Diabetic Retinopathy Images, International Journal of Innovative Research in Science, Engineering and Technology, Volume 3, Special Issue 3, March 2014.
[11]. C.Jagatheesh and C.Jenila, Automatic Detection and Classification of Diabetic Retinopathy Lesion Using Bag of Visual Words Model, International Journal of Scientific and Research Publications, Volume 5, Issue 9, September 2015.
[12]. D.L. Shechtman and L. A. Falco, Review of Optometry: Hypertension: More Than Meets the Eye, Vol.No: 144:09, 2007.
[13]. S. Hammond, J. R. Wells, D. M. Marcus and L. M. Prisant, Ophthalmoscopic Findings in Malignant Hypertension, The Journal of Clinical Hypertension, Volume 8, Issue 3, pages 221-223, March 2006.
[14]. N. Dey, A. Bardhan Roy, M.Pal and A. Das, FCM based blood vessel segmentation method for retinal image, International Journal of Computer Science and Network (IJCSN),Volume 1, Issue 3, June 2012.
[15]. A. Sopharak, B. Uyyanonvara, S. Barman and T. H. Williamson, Automatic detection of diabetic retinopathy exudates from non-dilated retinal images using mathematical morphology methods, Computerized Medical Imaging and Graphics 32 (2008) 720--727.
[16]. Lee, Tai S, Image Representation Using 2D Gabor wavelets, IEEE Transactions on Pattern Analysis and Machine Intelligence, 1996.
[17]. Kirsch, R. (1971), Computer determination of the constituent structure of biological images, Computers and Biomedical Research 4: 315– 328.doi:10.1016/0010-4809(71)90034-6
[18]. N. Otsu (1979).,A threshold selection method from gray-level histograms, IEEE Trans. Sys., Man., Cyber. 9 (1): 62–66. doi:10.1109/TSMC.1979.4310076
[19]. T.Carvalho, H. Jelinek, S. Goldenstein and J. Wainer, Points of Interest and Visual Dictionaries for Automatic Retinal Lesion Detection, IEEE Transactions on Biomedical Engineering, Vol.59, No.8, pp.2244_2253,Aug.2012.
[20]. J.Van Gemert, C.Veenman, A. W. M.Smeulders and J.M.Geusebroek, Visual word ambiguity, IEEE Transactions on Pattern Analysis and Machine Intelligence,vol. 32, Issue.7, International Journal of Scientific & Engineering.

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