ASSESSMENT OF COMPUTATIONAL METHODS FOR THE ANALYSIS AND GRADATION OF DIABETIC RETINOPATHY FUNDUS IMAGES

[1] R. RAVINDRAIAH, [2] S.CHANDRA MOHAN REDDY
[1] Research Scholar, Department of ECE, JNTUA, Anantapuramu, Andhra Pradesh, India
[2] Associate Professor, Department of ECE, JNTUA College of Engineering, Pulivendula, Kadapa Dist, Andhra Pradesh, India

Abstract : Diabetes Mellitus (DM) is a sporadic ailment resulted hyperglycemia and affect various vital human organ. Prolonged history of DM will result in Diabetic Retinopathy (DR), a vision impediment. The patho is characterized with swollen blood capillaries get ruptured and leak blood and protein particles into the retinal fundus. These exuded particles gets clotted and are termed as exudates and obstruct the light flow towards the retinal walls and may lead to impermanent or permanent vision loss. Hence proper medication with expert screening and management will help to slow the progression of the complication. The reliability of traditional diagnosis and screening methods is purely dependent on clinician's skills and expertise. It requires potential human labor and multiple resource management which make the disease diagnosis complex. With the advent of computer aided design tools various image processing methods are been presented by various authors for to detect the lesions in DR images and to classify them. Imaging devices can even be upgraded with these type of methods and can be helpful to make the clinician job more simple and effective. This paper reveals the literature of various work that are dedicated to DR detection, classification and gradation. The brief narration of these methods includes the objective, preprocessing, qualitative and statistical evaluation including the merits and demerits. Researchers can take the advantage of this literature paper so as opt a suitable approach either for up gradation or creation of novel works so as to overcome the flaws in the existing methods.

***Keywords* –Diabetes Mellitus (DM), Diabetic Retinopathy (DR), Retinal lesions**

I. INTRODUCTION

Diabetes Mellitus (DM) is a metabolic disorder that effects various vital organs of the body if not managed properly over long periods. Inability of the pancreatic cells to generate enough insulin or the resistance of the body to use insulin triggers various chronic organ malfunctioning [1-4]. Diabetic Retinopathy (DR), Diabetic macular edema (DME), Glaucoma and Cataract are the eye related issues originated due to DR. DR is a result of prolonged history of type 1 or type 2 diabetes and is usually found in working age and rural people. It is characterized into two predominant states termed as Non Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR is further classified into Mild, Moderate and severe NPDR. In Mild NPDR balloon like swells on the blood vessel (BV) walls are observed. These swelling are termed as microaneurysms (MA). Blockage of BV is observed in moderate NPDR and results in increased number of MAs and haemorrhages (HE). In severe NPDR new BVs are stimulated to emerge for to nourish the deprived retina. This new BVs are weak and may get ruptured leaking blood, protein and fat based particles get accumulated and obstruct the vision. This case is termed as Proliferative DR. The patho gets very complicated if these exuded particles get accumulated within macula (central part of retina) [5-6].

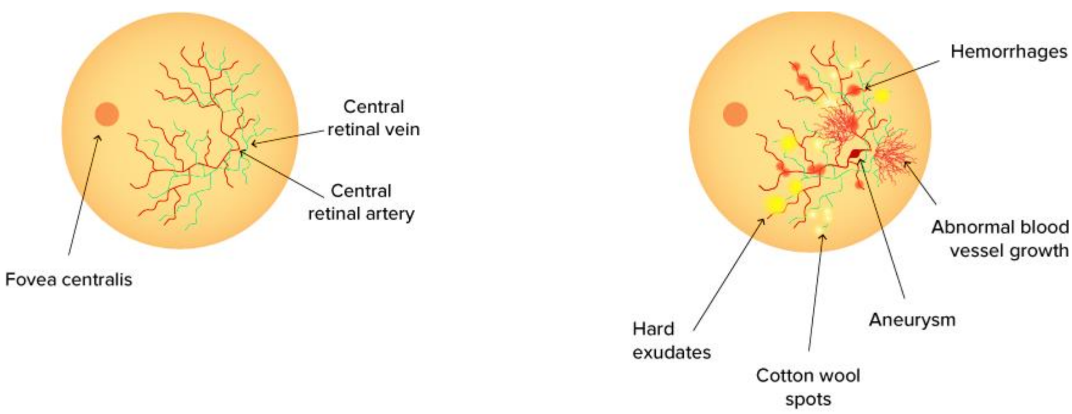

Figure 1: (a) Normal retinal images; (b) typical DR image [Image Courtesy: A Family Optician, U.K]

Figure 2: (a) Vision without DR (b) with Diabetic Retinopathy

Inter retinal thickening preferably at macula is a prime cause of DR. It is recommended to detect exudate sediments a near macula. Exudates are easily identifies as yellow or white patches with variable sizes, shapes and locations. Figure 1(a) represent the normal retinal fundus image and figure 1(b) represents a typical DR image. Figure 2(a) represent the vision with normal and DR affected eyes. Proper maintenance of DM and medication will help to suppress the symptoms and can help the victims for not to lose the vision permanently.

II. Literature review of Existing methods

Inclusion of Digital image processing (DIP) with medical imaging devises enables the easy analysis and assessment of the patho. It not only sophisticates the system but also reduces the labor of clinicians as the pathology is easily diagnosed and manually classified. This improves the reliable disease classification and eases the ophthalmologists labor. The following literature gives a qualitative analysis of DR screening systems in lesion detection and classification. These methods involve various DIP methods like edge and region based thresholding, Neural Networks (NN), Morphological operators, supervised and unsupervised classifiers [7].

Phillips.R.P et al., [8] detected soft and hard exudates using global and local thresholding methods from sharpened preprocessed images. Drusen and bare sclera areas are also identified by this DR computerized method and assessed accuracy, repeatability, reproducibility. Cotton wool spots (CWS) are unable to detect by this method. Gardner G.G et al. [9] generated Receiver Operator Coefficient (ROC) curves and characterized lesion features in contradiction to clinician resolution using Back propagation Neural Network (NN) classifier. Ege et al. [10] detected bright lesions using a sequence of template matching, region growing and thresholding methods and distinguished the disparity between exudates and CWS using Bayesian classifier. Wang. H et al. [11] performed illumination correction using brightness function and employed Minimum Distance Discriminant (MDD) classifier for DR grading. They concluded that multiple noise sources made their method to suffer with misclassification. A window-based recursive region growing algorithm combined with a novel Moat operator for lesion detection is introduced by Sinthanayothin. C et.al. [12], [43]. This method fails to detect faint exudates than hard ones.

A conventional morphological reconstruction for lesion detection is used by Walter.T et al., [13]. Prior to it a morphological filtering followed with watershed transformation is used to extricate OD. Osareh A. et al [14] performed coarse segmentation using FCM and features extracted from it are fed to multiple classifiers for comparative evaluation. They compared the performance of Neural Networks (NN), Linear Delta Rule, K-Nearest Neighbors and Gaussian classifier. They stated that NN classifier and Snake morphology has given optimal performance than the remaining classifiers. Identification of pale exudates is a lag in this method. Sinthanayothin C et al., [15] used highest intensity variation feature for OD extrication and BV using multilayer perception NN. Then spotted hard exudates using recursive region growing approach. Osareh A et al., [16] extended their previous paper [14] by employing lesion and image based classification. In both these papers the usage of FCM makes the system sensitive to outliers and noise sources. DR is identified using features like color, edge sharpness and geometric features is employed by Sanchez C.I et al., [17] with Kirsch operator. Slurred and contiguous exudate pixels with BV pixels are failed to be identified by this method.

Usher D et. al. [18] trained an Artificial Neural Network (ANN) and assessed sensitivity/ specificity pairs from multiple DR images. A two stage pixel level (Bayesian MAP classifier) and object level (Linear Discriminative Analysis) classification are used by Grisan et.al., [19] to classify multiple DR lesions. They concluded that pigmentation variation or shades of faint haemorrhages made the Bayesian classifier to lag with hard exudate detection. Bright lesions are detected by a three-step bottom-up method and Luv color space segmentation via an improved tow step FCM is demonstrated by Zhang X et. al. [20]. DR lesions are finally classified using a Support Vector Machine (SVM) classifier. Fleming A.D. et. al [21] described the use of local properties in a multi-scale morphological method and by thresholding a likelihood map a binary decision is conceded. Niemeijer M et. al., [22] devised a machine learning system using linear discriminant and k-nearest neighbor (kNN) classifier for DR classification. Giri Babu Kande et al., [23] addressed exudates detection using spatially weighted FCM and OD using a sequence of local variance, Lab color space morphology and geometric active contour model. A novel Fisher's linear discriminant analysis for hard exudate detection is introduced by Sanchez C.I et. al. [24]. Failure of pale exudate detection and validating clinical diagnosis with general conclusion is a flaw in this method. Various stages of DR is classified by Acharya U.R et al., [25] through SVM fed with features extracted from non-linear Higher Order Spectra (HOS). A sequence of morphological and thresholding method is used by

Sopharak.A et al. [26] for lesion detection. This system is unable to detect few faint exudates and fails to extricate few lesion pixels from BVs which possess high contrast similarities. Also they used ground truths generated using a specific software, which tends to authors bias with missed involvement of clinical expert. Sopharak.A [27] used median filtration and Contrast Limited Adaptive Histogram Equalization (CLACHE) in HIS color space and classified DR images using naïve bayes classifier. Suthammanas J et. al. [28] devised Retinal Thickness Analyzer (RTA) driven tele screening based automatic DR classification method. Acharya U.R et al., [29] classified DR using SVM fed with the extracted features from morphological operators. Sopharak et al. [30] allowed HIS image for noise filtration and stretched the contrast using adaptive histogram equalization in the first step. Then features from FCM are fed for nearest neighbor classifier for DR gradation. The presence of noise and artefacts make the system to suffer from identifying few pale exudates. Further a there exists a raise of false alarms due to the merge of non- exudate pixels with true exudates. The performance of Support Vector Machine (SVM), Multilayer perceptron (MLP), Radial basis function (RBF) are evaluated by Garcia M et al. [31] for to detect the existence of DR lesions. In [32] they enhanced green and luminosity components and identified the presence of exudates in DR images using a sequence of local, global and adaptive threshold techniques. Then Radial Basis Classifier is used to discriminate exudate lesions from the surrounding background pixels.

Sopharak et. al., [33] employed FCM method for DR lesion detection and validated them using clinical ground truths. In the initial step images contrast is stretched Blood Vessels (BV) are segmented using thresholding and Optic Disc (OD) using highest entropy value followed by morphological dilation and ostu thresholding. Sanchez et al. [34] demonstrated the use of intensity, edges sharpness for DR classification using a dynamic threshold based mixture models. They concluded that a 2D Markov Random Field (MRF) models with local information can be used to simplify the algorithm at the expanse of spatial correlation. Osareh A et. al [35] graded DR images by image and pixel level classification using Artificial Neural Networks (ANN) using the features from coarse FCM segmentation method and concluded their method fails to detect pale exudates. Sopharak. A. et al., [36] segmented non-dilated retinal images using FCM and morphological operators for coarse and fine results and the results are validated using ophthalmologists' hand-drawn ground-truths. They stated their method fails to work for noisy images and is fails to extract few faint exudates. Welfer et al., [37] used Luv color model and applied morphological and H-maxima transform for coarse to fine exudate detection. Their method suffers with poor specificity values. Sopharak.A, et al. [38] extended their previous work [36] by opting comparative analysis of FCM vs morphological approach and achieved greater accuracy with later method. A DR grading system is devised by Dupas B et. al. [39] using K-Nearest neighbor classifier (KNN) and morphological techniques.

Sanchez. C et al., [40] designed a Computer Aided Detection (CAD) system to classify DR images using linear discriminant classifier by incorporating spatial correlation and contextual features. Identification of pale and few bright lesions is a lag of this method. A novel Multiscale Frequency Modulation (FM) and Amplitude Modulation (AM) methods to discriminate DR images from normal and is proposed by Agurto et al. [41]. Their system is evaluated based on Receiver Operating Characteristic (ROC) value. Abramo .M.D et. al [42] demonstrated an pioneering method termed as EyeCheck algorithm and assessed optimum accuracy from several retinal images. S. Kavitha et. al., [44] proposed a non-linear diffusion based segmentation approach distinguished soft and hard exudates with the morphology and color histogram thresholding for to distinguish bright lesions from the background pixels. Akram et al. [45] verified dark and bright lesions using hybrid fuzzy classifier. Prior to it an average filter and thresholding methods are applied for the localization of OD and BV. Rocha et al. [46] used Scale Invariant Feature Transform (SIFT), Speeded up Robust Features (SURF) and k-means clustering to construct a visual word dictionary for the detection of bright and red lesions. Sharib ali et al. [47] generated an atlas image by wrapping the input images into atlas coordinatesand thresholded it to detect lesion candidates. Harangi.B et al. [48] performed retinal lesion counter detection and classification using an Active Contour Model (ACM) and adaptive boosted Naïve Bayes classifier. They improved the statistical features like sensitivity, specificity and accuracy with the use of ChanVese energy function minimization in [49] and revised their work in [50] by labeling the target lesions as true or false exudates.

Zhang et al. [51] addressed the use of classical and contextual features for lesion based classification and generated a lesion map to remove the false positives. They operated on multiple databases and attained optimum receiver operating characteristic curve AUC values. Pereira et al. [52] attained better performance than traditional Kirsch filter through the use of thresholding and Ant Colony Optimization methods in the detection of exudates in DR images. Medhi J.P. N et.al [53] applied logical AND operation on saturation plane and hue image obtained after normalization. Prior to it morphological operators and ostu thresholding is performed for OD and BV elimination. Harangi.B et.al., [54] demonstrated the use of Baye's classifier for lesion and image level classification. The classifier is fed with features obtained from a sequence of preprocessing steps like Chromaticity normalization, Grey-world normalization, Contrast enhancement, top-hat transformation, , illumination correction, Contrast-Limited Adaptive Histogram Equalization (CLAHE) and equalization). Imani.E et. al. [55] proposed a novel Morphological Component Analysis (MCA) method to distinguish exudates from blood capillaries. Then employed mathematical morphology and dynamic threshold methods to find the final exudate map. Shuang Yu et. al. [56] trained Convolutional Neural Networks (CNN) classifier, a deep learning method for pixel level DR classification by feedin g the features extracted from an ultimate morphological opening methods. Sil Kar. S et. al [57] segregated dark and bright lesions using morphological operations and a Differential Evolution algorithm. Prior to it morphological and Kernel induced FCM is used for the extrication of OD and BV. Then allowed the images to Laplacian of Gaussian (LoG) and Matched filtering and finally distinguished the candidate lesion using Mutual Information Maximization method. In [62] BV is extracted using a modified Fuzzy entropy maximization method and then graded various DR lesions. Gao Z et. al., [58] classified DR images using a deep Convolutional Neural Network method. They performed Data collection, preprocessing, augmentation, annotation, Model setup, deployment, and evaluated clinically the end results.

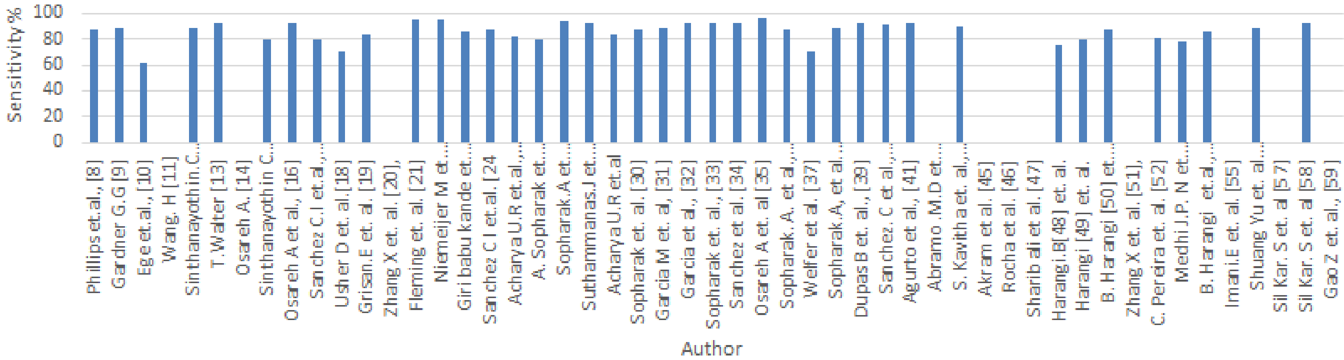

Figure 3: % Sensitivity of the existing methods

Figure 4: % Specificity of the existing methods

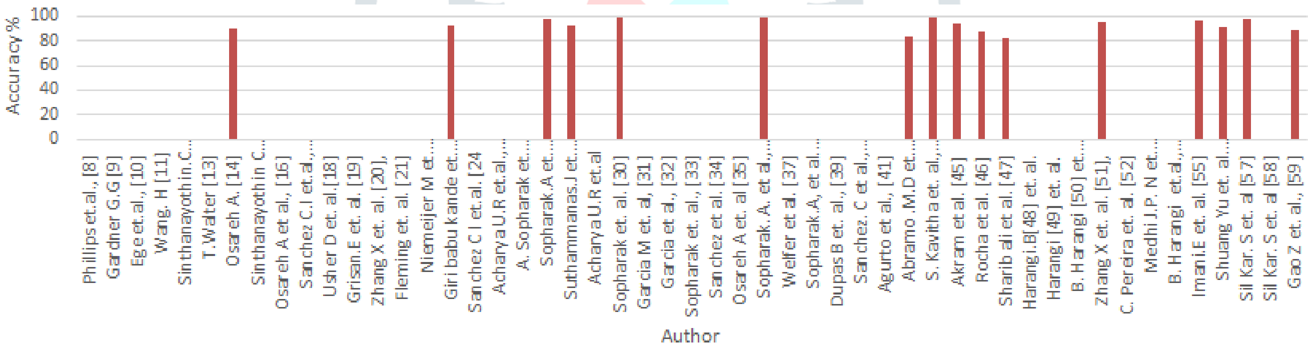

Figure 5: % Accuracy of the existing methods

Authors work briefed in this paper had used many public data bases preferably STructured Analysis of the Retina (STARE) [60], Digital Retinal Images for Vessel Extraction (DRIVE) [61], MESSIDOR [62], Hamilton Eye Institute Macular Edema Dataset (HEI-MED) [63], Kaggle Diabetic Retinopathy dataset [64], High resolution fundus (HRF) [65], Retinopathy Online Challenge (ROC) [66], Retinal Vessel Image set for Estimation of Widths (REVIEW) [67], E-Optha [68], Diabetic Retinopathy Database Calibration Level 0/1 (Diaretdb0 [69], Diaretdb1 [70]). Few authors had utilized both public and private databases provided by renowned hospitals and research labs. The mean Sensitivity, Specificity and Accuracy of these works are pictorially represented in Figures 3, 4, and 5 respectively. The elapsed time of all these methods are varied from few seconds to 30 minutes approximately based upon the number of stages utilized.

III. Conclusion

The evaluation of multiple works for lesion detection and classification is done in this paper. These works demonstrates the implementation of various methods, results obtained based upon specific author objective. Maximum all authors had implemented preprocessing steps like image enhancement, contrast stretch, filtration, illumination correction, normalization and so on in various color spaces in their preprocessing steps. Next concentration is made on localization of OD and removal of BVs. Most works include the usage of morphology and thresholding methods to extricate OD and BVs. Few methods are devised with unsupervised and supervised techniques and some of them includes both. All these methods had used public or private dataset provided by multiple resources and few of them are clinically validated and tried to automate the traditional medical imaging systems. Thus these methods had tried to improve the reliability of diagnosis and screening process and help to reduce the ophthalmologist's labor in disease classification and grading. The novelty, merits and demerits of these methods are also discussed in this literature and will be useful to researchers to opt specific approach either to upgrade or generate new innovative works.

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