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Gaussian Kernel Prompted Fuzzy C Means Algorithm with Multi-Object Contouring Method for Segmenting NPDR Features in Diabetic Retinopathy Fundus Images

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Abstract- Diabetic retinopathy is an ophthalmic inflammation caused by diabetes, which ends in visual defacement if not diagnosed earlier, and that has two types, namely Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR features are present in the earliest stage, and systematic detection of these features can improve the diagnosis of the disease severity formerly. Several detection methods exist previously. Still, there is performance lack on large datasets. The objective of this study is detecting NPDR features from diabetic retinopathy fundus images of large datasets with performance level. The study has investigated different fuzzy-based systems and to execute the objective; the GK_FCM approach was proposed, which integrates Gaussian Kernel function in conventional FCM. The execution has four phases. Initially, the input image undergoes preprocessing using green channel extraction, median filter to enhance the image quality and background removal is performed with extended minima transform technique, mathematical arithmetic operation and pixel replacement method to remove the outlier called Fovea (FV).

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Notes

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Shalini. R [α] & Sasikala. S [σ]

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Further, it is segmented for extracting NPDR features such as Micro-aneurysms (MA), Intra-retinal Hemorrhages (IHM), and Hard Exudates (HEXU) using Gaussian kernel with FCM of multiple parameters. Finally, the extracted features are visually enhanced on the original input image using post-processing operation of multi-class contour tracking (MCT) algorithm comprising different contouring measures. The experiments were done on two available online databases, namely DIARETDB0 and DIARETDB1. The performance of the proposed method is evaluated using the validation measures and compared with kernel induced fuzzy algorithms like MKFCM and LKFCM, comparatively the proposed GK_FCM method outperforms. Hence,the Gaussian kernel-based technique has been used for the analysis of the diabetic retinopathy fundus images to detect NPDR features of Diabetic retinopathy. The proposed work has given better results with an accuracy of 98.21%.

Keywords: non-proliferative diabetic retinopathy, minima transform technique, gaussian kernel, fuzzy C means, multiclass contour tracking algorithm.

I. Introduction

Diabetes mellitus ordinarily referred to as diabetes is a protracted disease that occurs when the pancreas is no longer able to create insulin, so the glucose in the blood are not being transferred into cells, which leads to high blood glucose. The prolonged blood glucose levels in the human body will cause several complications such as blindness, kidney failure, amputations, heart failure, stroke, etc. But among these conditions, blindness due to diabetes is considered an issue as the eyes is the essential organs of our body. The human eye is a significant body organ, but the care taken for

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this organ is emphasized very less in healthcare. There is no awareness among people about related complications like blindness caused due to diabetes. For instance, if people get blurry vision, they go for a computerized eye tests and wear specs considering it as a usual eye vision problem but not aware of the fact that it had been caused due to any internal disease like diabetes.

According to the Global statistics countersigned by the World Health Organization (WHO) [1], among 7.9 Billion of the current population, about 285.3 million people are visually impaired, out of which 246 million have low vision, and 39.3 million are blind. The reasons for blindness include glaucoma (12.3percent), age-related macular degeneration (8.7percent), diabetic retinopathy (4.8percent), childhood blindness (3.9percent) and trachoma (3.6percent). Among these eye problems, the one which harms the retina part of eyes due to diabetes is referred to as Diabetic Retinopathy (DR) [2]. There are numerous eye retinal disorders, but the most severe causes which doctors see in the retina are hypertension (High blood pressure level) and diabetes (high blood sugar level).

To be more precise, the complication in the retina due to high blood glucose level is more critical since they are symptomless. As per the review given by ophthalmology studies, the clinical and experimental evidence suggests that diabetic retinopathy and associated vision loss have several debilitating effects, including disruption of family functioning, relationships and roles, and deterioration of work prospects resulting in increased financial strain [3].

The tenacious high blood glucose level famishes the small blood vessels with in the retina due to an improper supply of oxygen. Hence this distortion to the retinal part of human eyes due to diabetes is called "Diabetic Retinopathy", which results in cloudy or blurred vision, and it is caused possibly among people with all types of diabetes such as type 1, type 2 and gestational. This complication results in visual impairment and even leads to blindness if undiagnosed and untreated.

There are two types of Diabetic Retinopathy [4], namely Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). The first type of DR disease is Non-Proliferative Diabetic Retinopathy [5], which is the earlier stage that weakens the walls of the blood vessels in retina, consequently the frail retinal blood vessels, begins to dilate and become irregular in diameter that leads to partial retinal mutilation. And this type can progress from mild to severe stage; as more blood vessels become leaky, then the retina begins to deteriorate, which leads to the advanced stage known as Proliferative Diabetic Retinopathy of Diabetic Retinopathy. And this stage is titled as second type of DR disease. It refers to the formation of new, abnormal blood vessels in the retina and these fragile new vessels often bleed, if it bleeds a little, a few dark floaters are seen, and if the bleeding is more, it might block all vision, at a point it can spoil both the central and peripheral (side) vision of the eyes.

Detection of the disease in its earlier stage can reduce the risk of disease severity by 100%. This study detects the first type of DR disease called Non-Proliferative Diabetic Retinopathy that causes different types of illnesses in the eye, such as Micro-aneurysms (MA), Intra-retinal Hemorrhages (IHM) and Hard Exudates (HEXU). The micro-aneurysm is tiny swellings that protrude from the blood vessel, which is the first sign of the NPDR type that appears as small red dots, and it is localized capillary dilatation which is usually s accular (round)[6].

The intra-retinal hemorrhages leaks blood into the retina, which is the second sign of the NPDR type; it is a 'dot' or' blot' or 'flame' shaped depending upon their depth within the retina. There are two layers of the capillary network in the posterior

Ref

1. https://www.geographyandyou.com/population/health/expansion-eye-health-services--essential-combating-diabetic-retinopathy/

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retina called nerve fiber layer and inner nuclear layer. Hemorrhage that occurs in the nerve fiber layer tends to be shape of 'flame'. In the inner layer, hemorrhages appear dot or blot shaped, aligned at right angles to the retinal surface, which is consequently viewed using an ophthalmoscope; the clinical differentiation between dot hemorrhages and micro-aneurysms is difficult and of little consequence since both are occurrences of background retinopathy[7].

The hard exudates are the protein fluid that oozed out from the blood vessel, which is the third sign of the NPDR type, and it forms a distinct yellow-white intra-retinal deposit, which varies from specks to larger patches, and that may evolve into rings known as circulates. Ultimately large confluent plaques can form. Hard exudates are extracellular lipid, which leaks from abnormal retinal capillaries, and forms a ring pattern around the leaking vessels. Hard exudates are found in the macular region, and as the lipids coalesce and extend into the central macula, vision can be severely affected[8].

So there is a necessity of an efficient system to discriminate and detect the affected regions with higher accuracy to assist the experts in diagnosing the disease severity earlier. In associate to spot the NPDR features from the fundus image, Non - Diabetic Retinopathy (Non-DR) features in the retinal fundus images have to be spotted and removed for the betterment of lesion identification. The Non-DR features are Blood vessels (BV), Optic disc (OD) and Fovea (FV) to be removed because the blood vessels and fovea features appear dark in color, so it falls in mismatch with the NPDR features like micro aneurysms and hemorrhages and the optic disc is the bright feature which falls in mismatch with the white color feature called exudates.

The retinal blood vessels are the central artery and vein in the retina, which provide and drain blood to and from the eye[9].The main blood vessels are supplied to the retina through the entry point called 'optic disc'. It is a vertical oval, with average dimensions of 1.76mm horizontally by 1.92mm vertically and placed at 3 to 4 mm to the nasal side of the fovea part of the eye[10]. The fovea is a tiny pit located in the macula of the retina that provides the clearest vision of all, and it is a small depression in the retina. The fovea is a black region inside the eye, lies in a fixed orientation and location relative to the optic disc. In the fovea, the layers of the retina spread aside to allow the light to fall directly on the cones that give the sharpest vision. So it is also called as the central fovea or fovea centralis[11].

In general, DR is assessed with single-field non-mydriatic fundus photography and graded according to the International Clinical Diabetic Retinopathy Disease Severity Scale 'HbA1c'[12]. HbA1c is glycated hemoglobin measured by a standardized tests using high-performance liquid chromatography. If higher the HbA1c value, then greater the risk of diabetes-related complications. The optimal HbA1c cutoff for detecting diabetic retinopathy is 49mmol/mol (6.6%) for mild and is 52mmol/mol ((6.9%) for moderate or severe. This grading is done twice in a year to detect the disease severity. But this conventional eye exam becomes a huge and complicated task as the number of patients suffering from the disease is increasing rapidly. Hence considering the importance of the disease severity and the complexity of the manual grading method, an emphasized screening system have to be developed with integrated and hybrid methods for accomplishing accurate diagnosis of the disease.

This proposed work detects the first type of Diabetic Retinopathy (DR) disease called Non-Proliferative Diabetic Retinopathy (NPDR) with its features from retinal fundus images. The task is very challenging because detecting the disease signs in the input includes major issues like noise (illumination or contrast) present in the image

Ref

8. https://www.glycosmedia.com/education/diabetic-retinopathy/diabetic-retinopathy-features-of-diabetes-hard-exudates/

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and also the variability in size, color, texture, and shape of the ROIs. Before detecting NPDR features, certain unwanted background features have to be removed to make the detection process more accurate. The study aims to find an appropriate segmentation method with better performance and to overcome the limitations mentioned earlier. The PCI, PEI, DSC measures of the proposed method and the existing works are being compared on two online databases, namely DIARETDB0 and DIARETDB1 [13]. The novelty of this work is comparing the proposed work with the performance of different kernel induced algorithms for segmenting the NPDR features in the Diabetic Retinopathy fund us images.

The GK_FCM algorithm incorporates the Gaussian Kernel function in conventional FCM to achieve the objective of this work. Initially, the input image undergoes preprocessing with green channel extraction and median filtering then background subtraction using extended minima transforms technique, mathematical arithmetic operation, pixel replacement method to eliminate the outlier called Fovea. Further, it is segmented for extracting NPDR features such as Micro aneurysms (MAs), Intraretinal Haemorrhages (IHMs), and Hard Exudates (HEXUs) by integrating Gaussian kernel with FCM on applying multiple parameters. The segmented features are dappled in the original input image using a multi-class contour tracking algorithm with different contouring measures as a post-processing operation.

II. Literature Review

Sasikala et al. [14] have proposed a novel medical image segmentation technique using the optimal threshold Reaction-Diffusion Active Contour model (RD-ACM) to identify Attention Deficit Hyperactive Disorder and cervical cancer-affected areas. In this method, the acquired input images are segmented using Thresholding, the connected components with label matrix algorithm, Heaviside and Dirac delta function; Level set evolution – Two- step splitting method. The proposed method shows better segmentation results. But the proposed RD-ACM gives better results for brain images when compared to cervical cytology images. So it has been found that theRD – ACM method can play a vital role in segmenting the regions of the brain images.

Sasikala et al. [15] has presented a review on various segmentation techniques used on hemorrhage images of both MRI and CT of the brain and analyzed the classification performance of different existing algorithms. Initially Preprocessing approaches are used to denoise the input, and numerous clustering techniques are applied to portray the existence of hemorrhage. Then Machine learning techniques are utilized to focus on issues that manipulate the prediction performance. The methods used for the hemorrhage detection in the input images are Decision Tree classifiers, Support Vector Machine, K-Nearest Neighbours, Thresholding techniques, Fuzzy C Means, Voxel-based outlier detection, Multilayer Perceptron. Among these methods, hemorrhage detection done with Fuzzy C Means results suggested that, to process more training samples, the prospect of this approach have to be modified.

Shyni et al. [16] have surveyed on segmentation algorithms for medical images of spinal cord tumor. The analysis carries various algorithms and techniques used on the medical images such as Fuzzy C-Means, Structural Similarity Index, Hybrid method (Text-Mining, cross-citation based). Data Mining techniques, Genetic Algorithm, support vector machine (SVM), vertebra object boundaries, learning algorithms optimization technique, Propagation segmentation (Prop Seg), level set(Dice similarity coefficient and Hausdorff distance), minimal path search algorithm, subsequent random-walk methods to identify the similarity and variations on the Spinal cord image analysis.

Ref

13. http://www2.it.lut.fi/project/imageret/

Shyni et al. [17] have proposed a work on spinal cord abnormality detection using preprocessing techniques like Median, Arithmetic, Gaussian, and Weiner. The preprocessed image underwent segmented with means, and fuzzy c means clustering algorithm followed by morphological operations and image manipulations have been performed. The performance comparison indices values of two segmentation algorithms witnessed that the proposed FCM method gives improved segmentation results with 84.5% precision.

Aafreen et al. [18] have developed an automatic system that can segment hemorrhage from brain MRI dataset using the Otsu and Watershed segmentation algorithm. For preprocessing the input MRI brain image, median filtering, and morphological operations like dilation and erosion are applied. The ROI have been segmented using Otsu and watershed algorithms. The proposed watershed algorithm have been validated with measures and resulted in an average 0.97overlap metric, average 0.94 precision, and average 0.94 recall, respectively. The results can be improved with variations in the preprocessing methods.

Shalini et al. [19] have presented a survey on the detection of diabetic retinopathy, which gives a review on different algorithms and techniques that have been used for detecting the lesions caused by diabetic retinopathy and also classifying its stages with higher accuracy. From this survey study, it is concluded that the DR lesion detection can be done using preprocessing techniques like green channel extraction, median filtering, and for the segmentation of DR lesions, the FCM algorithm performs better than other segmentation algorithms. Some unwanted features like blood vessels, optic disc needs to be removed to achieve better segmentation results. Finally, grading of lesions can be accomplished using classification algorithms like support vector machine, K nearest neighbor, etc.

Shalini et al. [20] have proposed a comparison work on the detection of hard exudates in diabetic retinopathy fundus images using the principles of Fuzzy-C Means and K-means algorithm. The method involves techniques like green channel extraction, median filter, Binary thresholding, K-means, Fuzzy-C-Means. The proposed comparison work shows that the segmentation of hard exudates using Fuzzy-C-Means is better with an accuracy of 95.05%. The results can be improved by inducing different types of filtering with the fuzzy method.

Alexandre et al. [21] have proposed an approach to segment the fovea a vascular zone of the retina images. The approach involves methods like grey-scale conversion, alternating sequential filtering, H-minima, Regional minima, connected component analysis, distance transform, watershed marker, and the final results have been evaluated in terms of accuracy, specificity, and sensitivity respectively of 0.9947, 0.9972 and 0.8442.

Hosanna et al. [22] have presented a paper to detect hard exudates feature in diabetic retinopathy affected image. Initially, the image is resized, contrast-enhanced with contrast limited adaptive histogram equalization, and intensity of enhanced image have been extracted. Further blood vessels are detected using green channel extraction, adaptive histogram equalization, and morphological operations. In the end, Fuzzy c means clustering (FCM) method segments the exudates in the preprocessed image. The performance measure results about 97.67% of accuracy, 91.108% of sensitivity, 97.95% of specificity.

Pallavi et al. [23] have proposed a segmentation algorithm using fuzzy-based algorithms. The input brain images have been preprocessed with Gaussian noise, salt, and pepper noise. Then the region of interest is segmented using mercer function-based

Ref

17. Shyni Carmel Mary S, Sasikala S, Identification of Abnormality in Spinal cord Using IP-FCM Clustering Algorithm, International Journal of Pure and Applied Mathematics. (2018) 119(16): 439-446.

fuzzy c means (KFCM) and Generalized Spatial kernel-based fuzzy c means (GSKFCM). The proposed methods KFCM and GSKFCM achieved an accuracy of 94.92% and 95.38%.

Ravindraiah et al. [24] have presented a paper for the detection of hard exudates in Diabetic Retinopathy images using Laplacian Kernel Induced Spatial FCM Clustering Algorithm. In this algorithm, laplacian kernel metric is induced into the kernel spatial FCM clustering algorithm for the segmentation of retinal fundus images. In existing methods, FCM and KFCM algorithms are very delicate to noise and other image artifacts because it doesn't have spatial information. To overcome this problem, the author has presented Laplacian kernel spatial FCM, which incorporates spatial information into its objective function and the fuzzy membership function. The performances of this algorithm have been evaluated on different Diabetic Retinopathy images, and the methodology is assessed using statistical measures like Sensitivity and Specificity. Thus LKSFCM method achieved Sensitivity of 99% and Specificity 89%.

Surendiran J et al. [25] have proposed a method to analyze the abnormal retinal images. In this work, the input images are subjected to hard exudates segmentation using the preprocessing techniques like grey-scale conversion; contrast limited adaptive histogram equalization then FCM clustering is applied for segmenting the candidate region. The results obtained have been compared with K-Means clustering, where FCM outperforms with an accuracy of 91.95%.

Rubya et al. [26] have proposed an automatic system that detects and classifies the Diabetic retinopathy lesions using fuzzy logic. Initially, the retinal fundus image is preprocessed with green channel extraction, median filter, contrast limited adaptive histogram equalization, and contrast stretching. Then linear spatial filtering, morphological filtering, transform operations, and binary Thresholding are applied to extract the features like blood vessels, optic disc, hard exudates, micro-aneurysms, and textural features like contrast, homogeneity. The extracted features are classified into respective classes using the fuzzy level set algorithm. The proposed system has higher performance with sensitivity, specificity, and accuracy up to 95.77%, 94.44%, and 95.63%, respectively.

Ganesh et al. [27] have proposed a new efficient system for the detection of microaneurysms in the retinal images. The technique uses Fuzzy-C-Means with the NLM-ADF algorithm. Initially, Fuzzy clustering is done for segmenting the pixels information further NLM in terms of the anisotropic filter is applied to improve identification of micro aneurysms in retinal images. The results show that the method improved the micro-aneurysms detection rate and got a ROC score of 0.427. The proposed methods have been tested on various simulated retina data repositories.

Sergio et al. [28] have proposed an effective method for detecting Non-Proliferative diabetic retinopathy features in color eye fundus images. The algorithm carries preprocessing of image using Green channel extraction, and contrast limited adaptive histogram equalization, the features like optic disc, blood vessels, fovea have been eliminated then the disease signs like micro-aneurysms and hemorrhages are detected by applying the image processing techniques such as alternative sequential filtering, H-minima transform, region minimum, Sobel and Prewitt filters along with morphological operations with the outcome of 87.69% sensitivity and 92.44% specificity.

Ganesh et al. [29] have presented a paper on identifying the microaneurysm feature in retinal images using the grey- scale conversion, Rotational Cross-Section Analysis, and Fuzzy C-Means Clustering Algorithm. The proposed approach has scored 0.435 ROC.

Ref

26. Rubya Afrin, Pintu Chandra Shill, Automatic Lesions Detection and Classification of Diabetic Retinopathy Using Fuzzy Logic, International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), IEEE. (2019): 527–532.

Venkatraman et al. [30] have proposed a system for the detection of Non-Proliferative Diabetic Retinopathy in Fundus Images by Wavelet Features. The system utilizes histogram equalization, candidate region extraction, wavelet features for detecting the diabetic retinopathy features by applying Mercer kernel, 2nd-degree polynomial kernel, 3rd-degree polynomial kernel and Gaussian kernel with the accuracy of 96.0%, 78.0%, 86.0%, and 84.0%.

Lama et al. [31] have presented work on dark lesion detection for Diabetic retinopathy using preprocessing methods like spatial calibration, illumination equalization, Mean Filter, Adaptive Contrast Equalization, color normalization then entropy-based Thresholding and multi-scale ring-shaped matched filter for optic disc removal. Finally, dynamic shape features like Relative area, Elongation, Eccentricity, Circularity, Rectangularity, Solidity are extracted, which is classified into lesions using a random forest algorithm with AUC of 0.899, 0.916, 0.976, 0.941 by testing four different databases.

Manoj et al. [32] have implemented a computer-aided detection system for the segmentation of Non-Proliferative diabetic retinopathy features and retinal features in color fundus images. The implementation comprises of algorithms like green channel, median filter; contrast limited adaptive histogram equalization, shade correction, Matched Filter-First Order derivative of Gaussian, Mathematical filtering, morphological operations, watershed segmentation, in-painting, h-extended minima algorithm, Selective Binary, and Gaussian Filtering Regularized Level Set and Signed Pressure Force algorithm. The proposed methodology for the segmentation of micro-aneurysms feature attained 90% accuracy, and exudate feature detection has given 93.41% accuracy.

The review done on detecting and segmenting the NPDR and Non-DR features renders various image processing methods. And these existing works have performed the segmentation process with preprocessed inputs, and some executions have been done on non-preprocessed image, and others employed kernels, parameter values to identify the object of interest (OOI) still there is some inability in achieving the accuracy of medical experts' outcome. There are a number of challenges in distinguishing and categorizing DR features; such as the presence of noise and outliers like the blood vessel, optic disc and fovea that are present in input images, the vacillating location of features, the similarity of shape and texture among some deformations (the micro-aneurysms and hemorrhages happen to occur with matching surface), which may direct to extracting redundant or ineffective features and results in low segmentation accuracy. This low performance consequently leads to improper diagnosis of the patient at the time of emergency states by the Physicians, which ultimately causes the severity of the retinal disease. The proposed FCM based segmentation evolves some initiatives to manage the inabilities found in the existing works.

The structures of the proposed work have been organized as follows; section 3 presents the theoretical background of the techniques used. Section 4 describes the experiments conducted to compare the different fuzzy algorithms adopted for NPDR features segmentation. The dataset descriptions have been given in division 4.1. Then the results are presented in division 4.2 and discussed in section 4.3 followed by conclusions and future work in section 5.

III. Theoretical Background

This paper has considered a fuzzy based algorithm for detecting the ROIs. This section presents a brief explanation of the proposed methodologies.

Ref

31. Lama Seoud, Thomas Hurtut, Jihed Chelbi, Farida Cheriet, Pierre Langlois JM "Red Lesion Detection using Dynamic Shape Features for Diabetic Retinopathy Screening, IEEE Transactions on Medical Imaging. (2015): 1 – 11.

a) Fuzzy clustering algorithm

The conventional Fuzzy based algorithms are used for partition the data points, where data point assigns memberships to each center as a result of which, for each iteration data point, belong to more than one middle point. It segments the ROI based on data point, which is chosen precisely among many data points, so the segmentation is more accurate.

For a given data set X={x1, x2, xn}, clustering algorithms partition the n data objects in X into c groups C={C1, C2, , Cc} based on similarity/dissimilarity metric [33]. The standard Fuzzy C Means algorithm [34] uses the Euclidean distance as an objective function to be minimized and expressed as the following equation:

$$J_{FCM}(U,V) = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{m} \parallel x_j - v_i \parallel^2 \quad (1)$$

Where vi is the cluster center of cluster Ci, m is the weighting exponent or the degree of fuzzifier in FCM. The fuzzy partition matrix have been expressed as

$$U = [\mu_{ij}]_{c\times n}, \ \mu_{ij} \in [0,1] \quad (2)$$

It is the membership degree of data object xjto cluster v_i, and

$$\sum_{i=1}^{c} \mu_{ij} = 1, \ \forall j = 1,2,3,\dots,n \quad (3)$$

In the iterations, the membership degree Pij and the cluster centers vihave been updated as

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}} \quad (4)$$

$$C_i = \frac{\sum_{j=1}^{n} \mu_{ij}^{m} x_j}{\sum_{j=1}^{n} \mu_{ij}^{m}} \quad (5)$$

We iterate (8) and (9) until the changes in the fuzzy partition matrix are very small, or some other stopping criterion has met.

III. Material and Proposed Methodology

In this section, we present the methodology adopted in the work, dataset, and proposed approach.

a) Material

i. *Dataset and Tools used*

The Experimentation of Non-Proliferative Diabetic Retinopathy features detection is conducted on The Processor AMD A8-7410 APU with AMD Radeon R5 Graphics HP Platform, 64-bit operating system, x64-based processor, 2.20 GHz Processor Speed and 4 GB Memory. The Segmentation Algorithm has been developed in the Matlab2014b-32 bit version. The dataset taken for this segmentation process have been obtained from eye care clinics and online repositories, namely DIARETDB0 and DIARETDB1 database, with a resolution of 93 x 71 in 24- bit depth PNG format. The databases contain 200 number of color fundus images for the experiment in which 189 contain signs of diabetic retinopathy.

ii. *Data Preparation*

Resizing: To standardize the image, resizing is carried out by the Bi-Cubic interpolation Area method [35], uses the biased average of four translated pixel values for each output

Ref

33. Kaile Zhou, Shanlin Yang, Exploring the uniform effect of FCM clustering: A data distribution perspective, Knowledge-Based Systems. (2016) 96: pp. 76-83.

pixel value then the input image is zero-padded and transformed into the positive horizontal direction by five-tenths of pixels.

$$p(x, y) = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij} x^i y^j \tag{6}$$

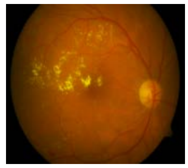

Fig. 1: Fundus retinal image

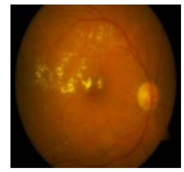

Fig. 2: Resized image

b) Methodology

The fundus input contains the unwanted features such as BV, OD, FV, and the NPDR features MA, IRH, HEXU, which are to be segmented, and they have been shown in Fig 2. The preprocessing technique improves the image quality and removes the Non-DR (unwanted) features in the image, then segmentation algorithms segments the NPDR features. The purpose of eliminating unwanted portions is reducing the false detection rates to achieve more accurate results in NPDR features segmentation.

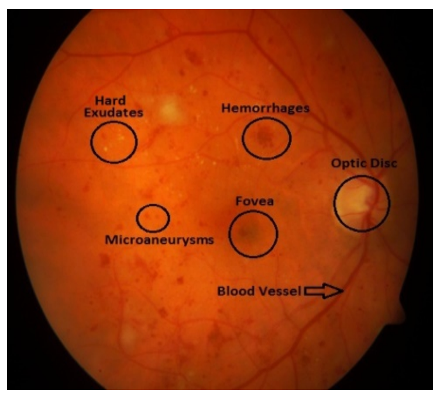

Fig. 3: DR-Fundus retinal image with NPDR and Non-DR Features

The goal of this work is implemented by following the proposed methodology represented in Fig 4, which consists of four-phases, namely standardization, preprocessing, segmentation, and feature recognition. The fundus retinal input image acquired from the DR database is standardized using the bi-cubic interpolation area method [35] for the resizing of the image. In the first phase, the resized image undergoes preprocessing by using the techniques like Green channel extraction, median filter for image enhancement then Binarized contour tracing (BCT), hybrid BINI Thresholding [36], extended minima transform algorithms are applied to detect the Non-DR features like blood vessels, optic disk, and fovea. In the second phase, the detected Non-DR features are removed from the input image using mathematical arithmetic operation (MAO) and pixel replacement method (PRM). The third phase carries out the segmentation on the preprocessed image to isolate the NPDR features like micro-aneurysms, intra-retinal hemorrhages, and hard exudates on applying Gaussian kernel prompted Fuzzy c means method. The fourth phase comprises marking of the segmented features in the input image using a multi-class contour tracking (MCT) algorithm to outline multiple regions of interests. The detailed executions of the algorithm have been explained below.

Ref

35. https://in.mathworks.com/help/vision/ug/interpolation-methods.html.

i. *Design*

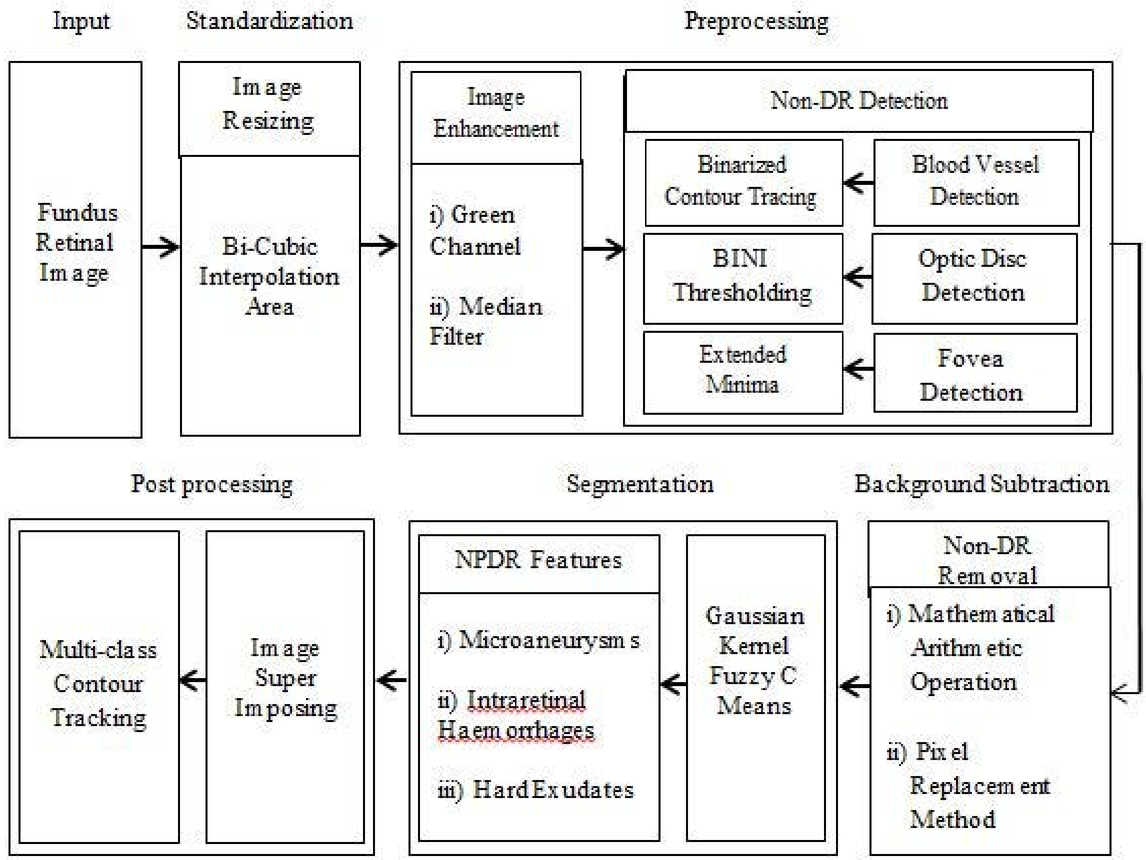

Fig. 4: Segmentation of NPDR features

ii. *Preprocessing*

Conventionally, the image data recorded or obtained through imaging systems like satellites, digital cameras. Though the images captured by a high configured fundus camera, there is a lack in contrast and brightness because of the illumination conditions. These errors are improved using applicable mathematical models, which are either definite or statistical models. This process has been termed as image preprocessing, and it has been performed for enhancing image structures for consequent analysis or image display. Image enhancement is the alteration of the pixel brightness values in an image to improve its visible effect, which is suited for human or machine interpretation. The enhancement process does not upturn the needed information in the data but just emphasizes certain specified image features. Hence the preprocessing is done for making the image more suitable for further processing. The enhancement techniques chosen for DR feature detection is resizing, channel extraction, noise filtering.

To enhance the fundus image segmentation process, the preprocessing operations are carried out using the green channel [37] of the RGB fundus image which project the DR features (ROI) more prominent than the Blue and Red Channels and unlike the other two channels (red, green), the green channel is neither lower illuminated nor over-saturated.

$$g = \frac{G}{R+G+B} \tag{7}$$

Ref

37. Noratikah Mazlan, Haniza Yazid, An improved retinal blood vessel segmentation for diabetic retinopathy detection, Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization. (2017): 1 – 10.

The equation represents red channel (R), green channel (G), and blue channel (B), respectively. The resulting image for the normalized green channel has been denoted by g.

The Median Filtering is a non-linear filtering technique [38] which removes noise while preserving the edges to enhance the region of interest.

$$y[m,n] = \mathrm{median}\{x[i,j], (i,j) \in \mathcal{w} \tag{8}$$

Where $\mathcal{w}$ represents a neighborhood value, given by the user, which is centered around the location [m, n] in the image.

The extended-minima transform (SMT) is a Thresholding technique which segments the fovea region. It is the local minima of h-minima transform. The regional transform replaces the pixel values to zero. The h-minima transform subdues all the minima in the intensity image whose depth is less than or equal to a predefined threshold value [39].

$$\mathrm{EM}_{(x,y)} = t(I, T) \tag{9}$$

Where, t is minima transform function
I denotes image
T is a threshold value

iii. *Segmentation*

The segmentation process is the significant difficulty in image processing, which is performed to dissect the ROIs. It subdivides the preprocessed image into some parts or objects until the object of interests is isolated, e.g. initially, dissection of the background from the image, then the foreground is segmented. Segmentation of images involves not only the discrimination between regions of interest and the unwanted portions but also the separation of more than one object of interest. One of the methods for such separation is known as FCM segmentation algorithm as follows;

Gaussian Kernel- based fuzzy clustering algorithm:

The kernel-based fuzzy clustering [40] introduced the kernel method into the FCM algorithm, which overcomes FCM's shortcomings in terms of insufficiency caused by data distribution characteristics to clustering results. Define a nonlinear map as

$$\phi : x \rightarrow \phi(x) \in F, \quad \text{where } x \in X, \ X \tag{10}$$

X denotes the data space, and F is the transformed feature space with a higher or even infinite dimension [41]. The objective function of KFCM has been defined as

$$J_{KFCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{m} \parallel \phi(x_j) - \phi(v_i) \parallel^2 \tag{11}$$

Where

$$\parallel \phi(x_j) - \phi(v_i) \parallel^2 = K(x_j, x_j) + K(v_i, v_i) - 2K(x_j, v_i) \tag{12}$$

We adopt the Gaussian function [42] as a kernel function,

$$\text{i.e} \quad K(x,v) = \exp\left[\frac{-(x-v)^2}{\sigma^2}\right], K(x,x) = 1 \tag{13}$$

Where σ is Gaussian kernel with multiple parameters, according to Eq.(12), Eq.(11) can be rewritten as:

Ref

38. https://www.sciencedirect.com/topics/engineering/median-filtering.

$$J_{GK\_FCM}(U,V) = 2\sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{m} \left[1 - K(x_j, v_i)\right] \tag{14}$$

Minimizing Eq. (14) under the constraint of μij.

$$\mu_{ij} = \frac{\left(1-K(x_j,\ v_i)\right)^{-1/(m-1)}}{\sum_{i=1}^{c}\left(1-K(x_j,\ v_i)\right)^{-1/(m-1)}} \tag{15}$$

$$v_i = \frac{\sum_{j=1}^{n} \mu_{ij}^{m}\ K\ (x_j,\ v_i)\ x_j}{\sum_{j=1}^{n}\ \mu_{ij}^{m}\ K(x_j,\ v_i)} \tag{16}$$

iv. *Post-processing*

The post-process has been performed for marking the segmented ROI in the input image. The segmented NPDR features are marked in the original input image using Contour-Base Object Tracking Algorithm [43]. Object tracking is considered to be an essential task in the computer vision field. The state of the contour, which shows the position of the segmented object, is defined using the centroid points. In the proposed work, six different segmented features have been pointed so the multi-class contour tracking algorithm is applied to mark the multiple areas of interest in the fundus input image.

c) *Results*

i. *Evaluation Metrics*

For internal and external evaluation of the proposed segmentation techniques, validation measures like Partition Coefficient Index (PCI), Partition Entropy Index (PEI), and Disc similarity Coefficient (DSC) have been calculated.

Partition Coefficient is the index value that determines the cluster partitions of two different techniques. The index value ranges between 0.894–0.9160.

$$PCI = \frac{1}{N}\sum_{p=1}^{M}\ \sum_{i=1}^{N}\ \mu_{iM}^{2} \tag{17}$$

Partition Entropy is the index value that determines the entropy of cluster partitions of two different techniques. The index value ranges between 0.1989–0.2703.

$$PEI = \frac{1}{N}\sum_{p=1}^{M}\ \sum_{i=1}^{N}\ \mu_{iM}^{2}\log_2(\mu_{iM}) \tag{18}$$

Dice Similarity Coefficient is a performance analysis method based on the spatial overlap between two different segmentation processes of the same image. It is the same as f-score, considered as an accuracy measure that counts all the true positives, false positives and true negatives.

$$DSC = \frac{2.TP}{2.TP+FP+FN} \tag{19}$$

Where TP, FP, TN, FN are True Positive, False Positive, True Negative, and False Negative, which have been defined as the number of pixels classified correctly and incorrectly in abnormal existence and normal image by the proposed method.

Ref

43. Chirag I. Patel, Ripal Patel, Contour Based Object Tracking," International Journal of Computer and Electrical Engineering. (2012) 4(4) : 525-52

Notes

Table 1: Performance measures of NPDR Features Segmentation

Methods	PCI	PEI	DSC
MK_FCM	0.90	0.23	0.78%
LK_FCM	0.91	0.48	0.89%
Proposed GK_FCM	0.94	0.79	**0.98%**

ii. *Implementation Outcome*

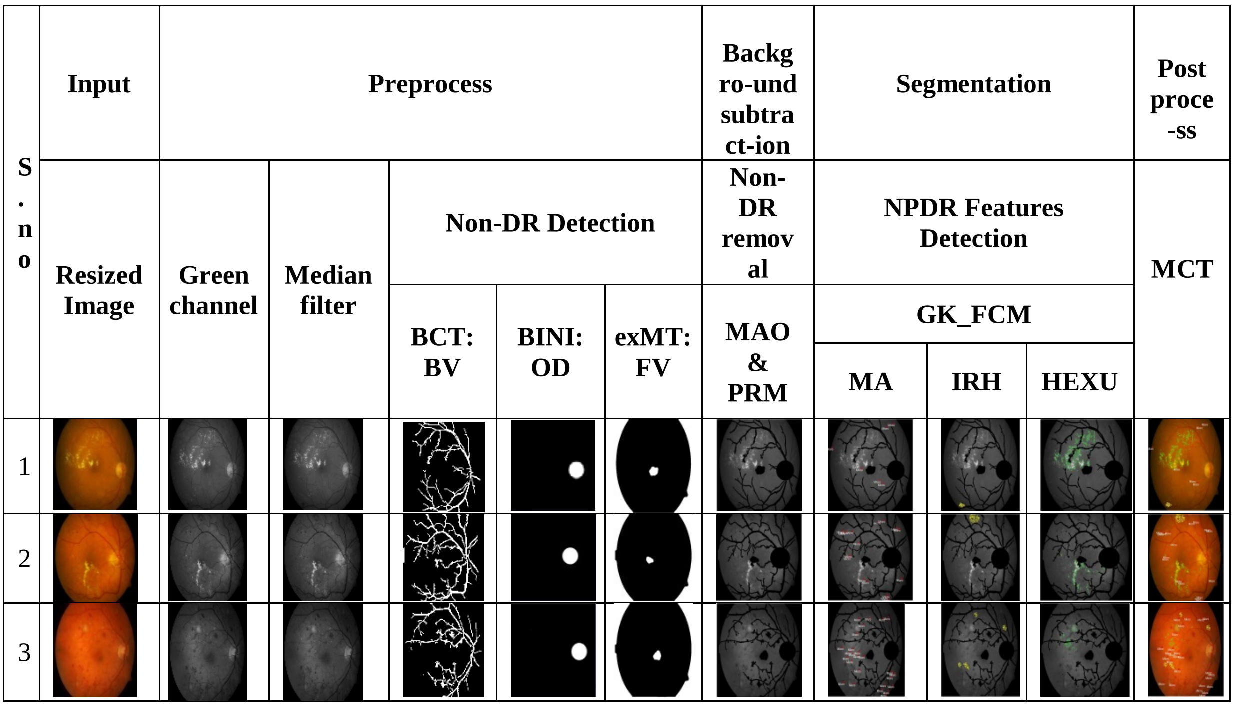

Fig. 4: NPDR features Segmentation

iii. *Discussions*

NPDR stage is the sign of leaking blood vessels that drop out blood, fatty deposits, and fluids on the retina. Segmentation of NPDR features is a necessary process to support the expert in the analysis of disease to obstruct its severity as earlier as possible. At first, the acquired inputs have been standardized by resizing it to 512 X 512 dimensions, as portrayed in fig.3, column 2. The purpose of resizing is to make images more receptive to accomplishing further processing and for complete visibility on screens of different devices. Then the resized images undergo the preprocessing operation using green scale conversion as it enhances the fundus image; it is done by extracting the green channel of the color fundus image, which projects the DR features more noticeable than the Blue and Red Channels. Then median filtering is performed on the green scale image to suppress the noise present in the inputs that have been represented in fig.2, column 3.1, and column 3.2.

This green Channel image is applied with the background subtraction process using numerous image processing techniques to detect and remove the unwanted Non-DR features like Blood Vessel, Optic Disc, and Fovea so that the NPDR features are more projective. The first feature Blood Vessel is detected using the binarized contour tracing (BCT) method and the second feature Optic disc is segmented using BINI Thresholding are shown in columns 3.3 and 3.4, which has been already done, and described in the previous work [36]. The proposed work: detected the third feature called Fovea feature using extended minima transform method, as shown in column 3.5. Then these three detected features are removed from the input image using the mathematical arithmetic operation (MAO) and pixel replacement method (PRM) in column 4. Further, this image is given as input for the segmentation process for segmenting the NPDR features like MA, IRH, and HEXU using Gaussian kernel-based fuzzy c mean algorithm, which have been shown in column 5.1, 5.2, 5.3. Finally, the segmented features are plotted in the fundus input image using a multi-class contour tracking (MCT) algorithm and the result have been shown in column 6.

The first algorithm [30] in table 1 called Mercer-Kernel induced Fuzzy C Means, where clustering is done by FCM integrating with Mercer function to cluster the data points. The mercer function is the kernel method used in the segmentation algorithms to segment the ROI that is unlabeled, and it is suitable for a cluster with spherical ring shape by default. Also the function needs prior information of the cluster shape. If the cluster shape is not specified priory, and ROI outline have not been fixed with default cluster shape, then a grouping of data points in segmentation process flops. The second algorithm [24] in table 1 is Laplacian-kernel based Fuzzy C Means, which uses the kernel with Cauchy distribution to deploy more frequency components which overlook the noises present in the image. But this distribution is not time adaptive in handling the large dataset since it uses a single parameter. The fourth algorithm in table 1 is the proposed Gaussian-kernel based Fuzzy C Means, and this algorithm carries normal distribution of pixels to handle the noise present in the image that makes a grouping of identical pixels more contented. Here the kernel is employed with multi-parameters, which is suitable for handling large datasets with less time and also performs better in multiple ROI segmentation. Hence, the proposed GK˙FCM method has given better results than the existing fuzzy C means algorithms for segmenting multiple ROI and achieved accuracy of 98.21%.

The validation measures of the proposed segmentation algorithms have been evaluated in terms of PCI and PEI. The values are 0.89 and 0.51 for FCM, 0.90 and 0.23 for MKFCM, 0.91 and 0.48 for LKFCM, 0.98 and 0.79 for GK˙FCM. The performance analysis of NPDR feature segmentation using FCM gives 91.95% accuracy, MKFCM gives 78.0% accuracy, LKFCM gives 90.88% accuracy, and the GK˙FCM algorithm gives 98.21% accuracy. The evaluation results have been shown in table 1, and the graph for the resulted values have been given in Fig 4. The results show that the proposed method GK˙FCM gives a better result.

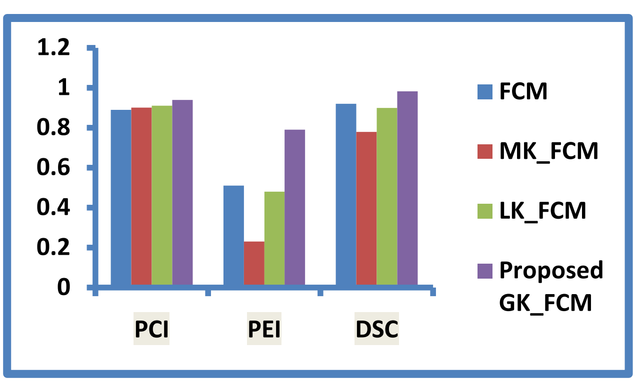

Fig. 3: Comparison of accuracy of NPDR feature segmentation algorithms

Ref
30. Venkatraman K, Programmed Detection of Diabetic Retinopathy in Fundus Images utilizing Wavelet Features, Journal of Chemical and Pharmaceutical Sciences. (2016) 9(2): E59 – E63.

Notes

V. Conclusion and Future Work

The earlier identification of the diabetic retinopathy and its features is more necessary to avoid the precarious condition. So, the segmentation of NPDR features using Fuzzy based algorithm in the fundus images has been implemented by resizing the input image using a bi-cubic interpolation method. Then preprocessing techniques like green channel extraction and median filter have been used for highlighting the image features for subsequent exploration. Further background subtraction have been done, which applies algorithms like binary contour tracing, BINI Thresholding, extended minima transform, mathematical arithmetic operation, and pixel replacement for detecting and removing unwanted features like blood vessels, the optic disc which ignores the false positives and enhances the area of interest to be segmented. For segmenting the ROI so-called NPDR features like micro-aneurysms, intra-retinal hemorrhages, and hard exudates, Gaussian kernel-based Fuzzy C means algorithm have been applied. In this segmentation algorithm, the Gaussian function identifies all the pixels with equal distribution also filter has been set, which improves the features detection process more efficient and accurate. The proposed work has achieved 98.21% accuracy. Future work focuses on feature extraction of Diabetic retinopathy fundus images with improved performance.

Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Dataset used in this work are available in online DIARETDB0 database also gathered from Sankara Nethralaya Hospital, Chennai. "All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards."

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